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Water Demand Forecasting In Al-Ain City, United Arab Emirates

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WATER DEMAND FORECASTING IN AL-AIN CITY, UNITED ARAB EMIRATES

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This thesis is submitted in partial fulfilment of the requirements for the degree of Master of Science in Civil Engineering

Under the Supervision of Dr. Mohamed Mostafa Mohamed

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Declaration of Original Work

I, Hebah Ibrahim Younis, the undersigned, a graduate student at the United Arab Emirates University (UAEU), and the author of this thesis entitled "*Water Demand Forecasting in Al-Ain City, United Arab Emirates*", hereby, solemnly declare that this thesis is my own original research work that has been done and prepared by me under the supervision of Dr. Mohamed Mostafa Mohamed, in the College of Engineering at UAEU. This work has not previously been presented or published, or formed the basis for the award of any academic degree, diploma or a similar title at this or any other university. Any materials borrowed from other sources (whether published or unpublished) and relied upon or included in my thesis have been properly cited and acknowledged in accordance with appropriate academic conventions. I further declare that there is no potential conflict of interest with respect to the research, data collection, authorship, presentation and/or publication of this thesis.

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Abstract

Al-Ain city is the second largest city in the Emirate of Abu Dhabi and the third in the United Arab Emirates (UAE). Currently, desalination plants are the only source of municipal water in Al-Ain city with an average daily supply of 170 MIG. The expected natural population growth, in addition to future projects, will certainly put additional stress on the water resources in the city. Therefore, Al-Ain city seems to be in an urgent need for estimations of future water demands for achieving sustainable development.

The main aim of this thesis is to introduce a water demand forecasting model to predict water needs for Al-Ain city under different scenarios in the coming 15 years (till 2030), in order to achieve water resources sustainability in light of the expected increase in the water demands. A water budget model (WBM) for Al-Ain city is developed in this thesis for the years 2012 and 2030, respectively. Some uncertainties in the reading and recording data were discussed in this thesis, in addition to the uncertainties in the prediction.

Two different models were adopted to forecast water demand of the different sectors using IWR-MAIN program, which are "Constant Use Rate Model" and "Linear Forecasting Model". The verification of simulation models is conducted with two different base years. Three main groups of scenarios are introduced in this study, including water demand predictions assuming "business as usual", population growth sub-scenarios, and amended losses sub-scenarios. Results showed that the water demand is expected to be almost doubled in 2030. Following the same consumption trends, the quantity of water outflow from the city in year 2030 is expected to be 50% than the water inflow to the city by model 1, while it is almost 35% in model 2.

Keywords: Water demand, water budget model, IWR-MAIN, water forecasting in Al-Ain, constant use rate model, linear forecasting model.

Title and Abstract (in Arabic)

تقدير الاحتياجات المائية المستقبلية في مدينة العين، في دولة الإمارات العربية المتحدة

الملخص

العين هي ثاني أكبر مدينة في إمارة أبوظبي، والثالث في دولة الإمارات العربية المتحدة. في حين، الإمارات العربية المتحدة تقع في المنطقة المدارية الجافة. حالياً، محطات تحلية المياه هي المصدر الوحيد لمياه البلدية مع متوسط الطلب اليومي (MIG 170). النمو السكاني الطبيعي المتوقع، بالإضافة إلى المشاريع المستقبلية، بالتأكيد سوف يضع ضغوطا إضافية على موارد المياه في المدينة. لذا، تبدو مدينة العين في حاجة ماسة للتقديرات الطلب على المياه في المستقبل نحو تحقيق التنمية المستدامة.

والهدف الرئيسي من هذه الرسالة هو وضع نموذج تنبؤ الطلب على المياه لتقدير الاحتياجات المائية في مدينة العين في 15 سنة القادمة (حتى 2030)، من أجل تحقيق الاستدامة للموارد المائية في ضوء الزيادة المتوقعة في الطلب على المياه. بالإضافة إلى ذلك، وصفت هذه الدراسة نموذج الميزانية للمياه (WBM) لمدينة العين في السنوات 2012 و2030. وتمت مناقشة بعض الشكوك في قراءة البيانات وتسجيلها، بالإضافة إلى عدم اليقين في التنبؤ.

تم تنفيذ نموذجين مختلفين للتنبؤ الطلب على المياه لمختلف القطاعات من قبل برنامج IWR-MAIN، وهم معدل الاستخدام الثابت والتنبؤ الخطي المحدد. وتم التحقق من كفاءة النموذجين عن طريق استخدام قاعدة بيانات لسنة أساس 2008 و2010. إلى جانب ذلك، تم تقديم ثلاثة سيناريوهات في هذه الدراسة، وهي التنبؤ الطلب على المياه باستخدام برنامج

IWR-MAIN، تنبؤ المياه على أساس سيناريوهات النمو السكاني، وتوقع الطلب على المياه تبعا لسيناريوهات خسائر الماء أثناء التوزيع. هذه الدراسة ناقشت نموذج الموازنة المائية للحصول على تدفق المياه داخل / خارج طبقة المياه الجوفية. بإيجاز، أظهرت نتائج الدراسة أن تقدير الطلب على المياه يكون تقريبا الضعف في عام 2030، فضلا عن الضعف في حجم السكان. أيضا في عام 2030، يوضح نموذج التنبؤ الأول أنه من المتوقع أن يكون تدفق المياه من الخزان الجوفي أكثر بمعدل 50 % من تدفق المياه إلى الخزان الجوفي، في حين من المتوقع أن يكون أكثر بمعدل 35 % في نموذج التنبؤ الثاني.

مفاهيم البحث الرئيسية: الطلب على المياه، نموذج الميزانية للمياه، تقدير المياه في العين، IWR-MAIN، معدل الاستخدام الثابت، التنبؤ الخطي المحدد.

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Special thanks go to my parents, brothers, and sisters who helped me along the way. I am sure they suspected it was endless.

Dedication

This thesis is dedicated to:

The sake of Allah, my Creator and my Master,

My great teacher and messenger, Mohammed (May Allah bless and grant him), who taught us the purpose of life,

My great mother, who never stops giving of herself in countless ways,

All the people in my life who support me.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

UAE	United Arab Emirates
ARIMA	Autoregressive Integrated Moving Average
ANN	Artificial Neural Network
SVM	Support Vector Machine
LQE	Linear Quadratic Estimator
IFCS	Intelligent Forecasters Construction Set
GCC	Gulf Cooperation Council
BCM	Billion Cubic Meters
MCMY	Million Cubic Meters per Year
AD	Average Day
SEKID	South East Kelowna Irrigation District
HLSALOA	Hidden Layer Sigmoid Activation Linearly Activation Output
API	Antecedent Precipitation Index
CT	Current Trends
MRI	More Resource-Intensive
MGD	Million Gallons per Day
DU	Distribution Uniformity
PF	Plant Factor
SAR	Simultaneous Autoregression
eTS	Takagi-Sugeno
IFCS	Intelligent Forecasters Construction Set
FL	Fuzzy Logic
MAPE	Mean Absolute Percentage Error
MLP	Multi-Layer Perceptron

RBF	Radial Basis Function
ANG	Artificial Neural Genius
OG	Overall Genius
CNN	Computational Neural Networks
EKF	Extended Kalman Filter
IWRM	Integrated Water Resource Management
SPSS	Statistical Package For Social Science
ARMSE	Average Root Mean Square Error
SDARE	Standard Deviation of the Absolute Relative Error
AARE	Average Absolute Relative Error
ADWEA	Abu Dhabi Water & Electricity Authority
AADC	Al Ain Distribution Company
ADDC	Abu Dhabi Distribution Company
TRANSCO	Abu Dhabi Transmission and Despatch Company
FAPCO	Fujairah Asia Power Company
ESWPC	Emirates Sembcorp Water and Power Company
AMPC	Al Mirfa Power Company
GTTPC	Gulf Total Tractebel Power Company
ECPC	Emirates CMS Power Company
SCIPCO	Shuweihat CMS International Power Company
TAPCO	Taweelah Asia Power Company
APC	Arabian Power Company
RPC	Racing Power Company

Chapter 1: Introduction

1.1 Overview

A public water supply delivers volumes of water to customers (such as: residents, businesses and other uses in urban area) within a certain period of time (Billings and Jones, 2008). Forecasting is a planning tool that helps management in its tries to deal with the uncertainty of the future. It relies mainly on data from the past and present and one or more techniques to estimate outcomes into the coming months or years. However, forecasting depends on certain assumptions based on the experience, knowledge and judgment.

Water demand forecasting is very significant in any country to achieve sustainable development especially for countries that have lack in water resources. Several approaches can help to forecast water demand in both long-term and short-term. Long-term forecasting is essentially suitable for infrastructure and capital planning. On other hand, short-term forecasting is beneficial for setting water rates. Generally, UAE has one of the highest per capita water consumption rates. Peck (2010) mentioned that Abu Dhabi’s per capita water use is more than twice the international average. So, a water demand forecast is fundamental in water resources planning to meet anticipated future demands and the accurate forecasts help to ensure to provide an appropriate amount of water supply, and to provide safe and ample water at minimum cost.

The main aim of this thesis is to introduce a water demand forecasting model to predict water needs for Al-Ain city till 2030. Al-Ain city is the second largest city in the Emirate of Abu Dhabi and the third in the UAE. The expected natural population growth, in addition to future projects, will certainly put additional stress on the water resources in the city. Forecasting is very important in many types of organization since prediction of future events must be incorporated into the decision-making process. Therefore, Al-Ain city seems to be in an urgent need for estimations of future water demands towards achieving sustainable development. Analyzing a past data would be a major concern in forecasting a future events. So, in this thesis, several variables are considered such as water quantity, population size, temperature, and rainfall.

1.2 Study Objectives

The main objective of this thesis is to introduce a water demand forecasting model to predict water needs for Al-Ain city in the coming 15 years, in order to achieve water resources sustainability in light of the expected increase in the water demands. Moreover, the objectives include:

1. Assessment of the current available water resources in the city and the demands of the different sectors (such as: industrial, commercial, and agricultural, etc.)
2. Evaluation of the current water system in the city including identification of current stakeholders representing different water sectors (such as: users, top officials, managers, authorities, investors, regulators, planners, etc.)
3. Reviewing the current regulation and policies in city's water management practice.
4. Evaluation of the influence of the announced development projects on water demand; structure of water industry; inter-agencies relations, regulations and policies related to water management; and economical/financial planning.
5. Prediction of the water demands for the city till year 2030 under different management scenarios.

1.3 Forecasting Methodologies

Several models and methods are available for urban water demand forecasting and they could be qualitative or quantitative forecasting. The qualitative forecasting techniques are subjective and they used to forecast future data based on the opinion and judgment of consumers and experts. So, they are suitable when past data are not available. On the other hand, the quantitative forecasting models are suitable when past data are available because they are used to forecast future data based on the past data (Yanyan, 2012). In this thesis, quantitative forecasting methods are selected and each method is discussed below.

1.3.1 Time Series Analysis Method

Donkor et al. (2012) mentioned that a time series models, or what is known as extrapolation forecasts, is a sequence of numerical data points, normally consisting of successive measurements made over a time interval. While, time series forecasting is the use of a model to predict future values based on past observed values. Basically, time series analysis has two classes of components which are trend and seasonality, however, the eight generic time series profiles depicted in Figure 1. Various methods are obtainable to analyze data by using time series for instance; linear or (most often) nonlinear component that changes over time, univariate (a single data set) and multivariate (two or more data sets). Generally, one common approach in time series is the Box–Jenkins method which applies ARIMA method that can be used for univariate or multivariate analysis to find the best fit of a time-series model (Statsoft, 2015).

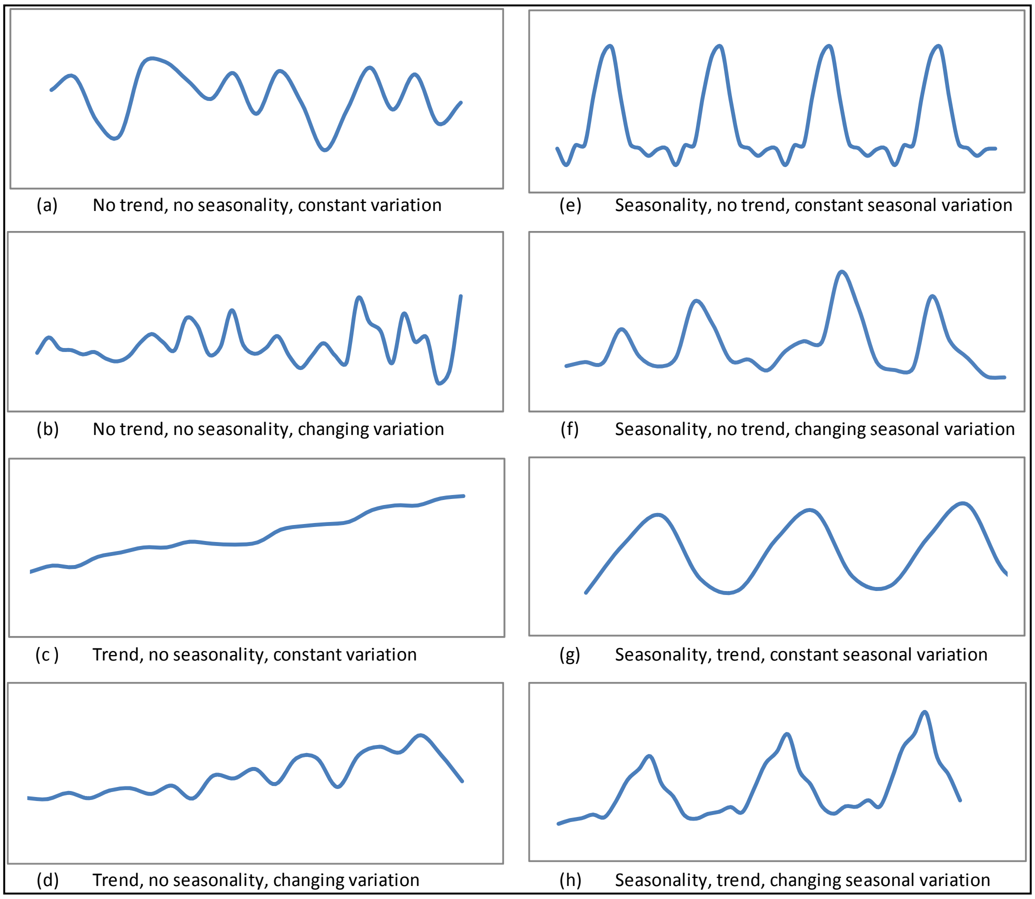


Figure 1: Profiles of Generic time series (Donkor et al., 2012)

1.3.2 Regression Analysis Method

Regression analysis is statistical approach for estimating the relationships between one or more independent variables. Also, regression analysis uses a group of random variables, and tries to explore a mathematical relationship between them. Commonly, regression analysis is used for prediction and forecasting. It also known as curve fitting or line fitting because it can be used in fitting a curve or line through a scatter plot of paired observations between two variables. So, regression line is usually determined quantitatively by a best fit (the differences in the distances of data points or observations from the curve or line are minimized). There are two different types of regression analysis which are simple linear regression and multiple linear regression (Mohamed and Al-Mualla, 2010). Linear regression technique uses to explain or predict the outcome; one independent variable is plotted on the x-axis and another dependent variable is plotted on the y-axis. Figure 2 illustrates an example of a linear regression line. Furthermore, multiple regression technique uses two or more independent variables to predict the outcome. Additionally, the formula of each type of regression is given by Investopedia (2015) as follow:

- Linear Regression: $Y = a + b\,X + u$ (Eq. 1)

- Multiple Regression: $Y = a + b_1 X_1 + b_2 X_2 + b_3 X_3 + \ldots + b_t X_t + u$ (Eq. 2)

Where:

Y= the variable that we are trying to predict

X= the variable that we are using to predict Y

a= the intercept of regression line

b= the slope of regression line

u= the regression residual.

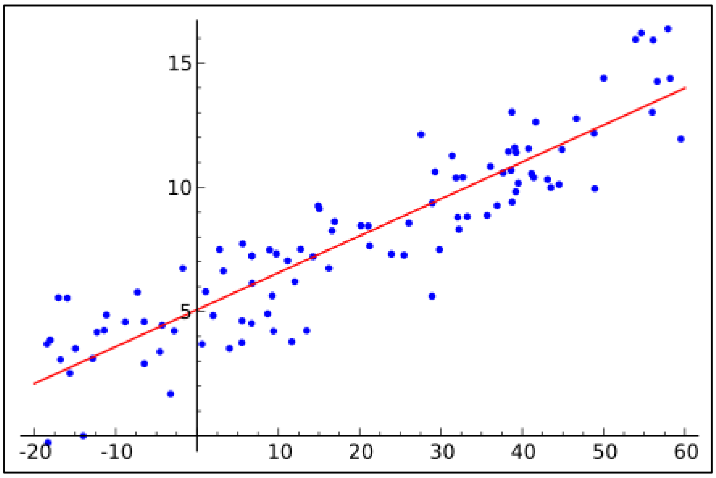


Figure 2: Example of linear regression line (Sewaqu, 2010)

1.3.3 Artificial Neural Network Technique

Artificial neural network (ANN) is provided by the inventor ‘Dr. Robert Hecht-Nielsen’. He describes a neural network as “*a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs*” **(**Cs.wisc., 2015). Artificial neural network (ARR) or neural network is advanced methods classified as nonparametric (Donkor et al., 2012). ANNs are processing devices (algorithms or actual hardware) are taken into consideration the nonlinear statistical data modeling tools where the relationships between inputs and outputs are modeled. In addition, an ANN has advantages such as it works for capturing associations or discovering consistencies within a set of patterns and it uses as a random function approximation tool. Also, ANN takes data samples instead of entire data sets to obtain solutions which saves both money and time. ANN has three layers of nodes that are interconnected. Those nodes represent an artificial neuron which is the first layer contains input neurons where external information is received. The output data from first layer send to second layer by neurons and then to third layer (Mohamed and Al-Mualla, 2010). Figure 3 illustrates the three layers of artificial neuron and the arrows represent a connection from the neuron’s output to the input of another.

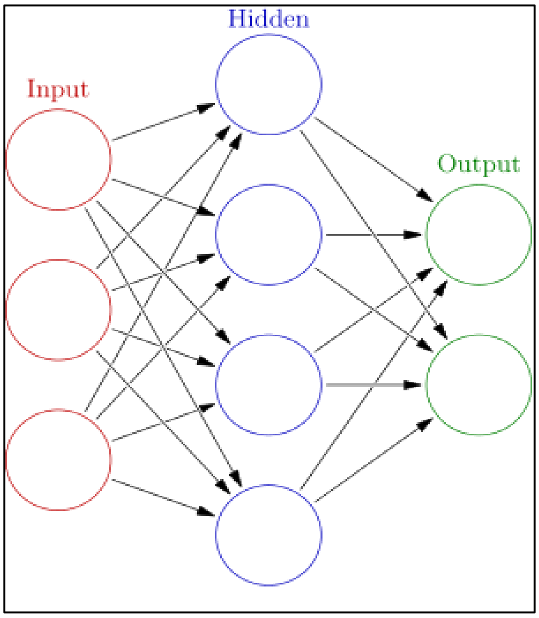


Figure 3: Schematic diagram of an Artificial Neural Network (Lee and Antonio, 2015)

1.3.4 Fuzzy Logic Method

Zadeh (1965) developed the concept of fuzzy logic. Klir and Yuan (1995) explained that a fuzzy logic method is non monotonic logic. It is a suitable method for human reasoning so, it represents some form of incomplete or uncertain data. Also, fuzzy logic is planned to obtain the best possible decision given the input by considering all available information and it can be indicated with degrees of truthfulness and falsehood. Moreover, fuzzy logic can be used in other artificial intelligence applications to produce fuzzy systems that are able to adapt and learn.

1.3.5 Support Vector Machines

Shen et al. (2015) indicated that a support vector machine (SVM) algorithm was developed by Vapnik (1963). SVM is a learning technique with accompanying learning algorithms that recognize patterns and analyze data. The basic idea of SVM model is representing a set of input data as points in space, mapped so that the separate groups are divided by a clear gap. Then, new groups transfer into that same space and expected to belong to a group based on which side of the gap they fall on. Figure 4 shows the basic idea behind Support Vector Machines (SVMs) (Statsoft, 2015). The left side illustrate the original objects mapped (transformed) using a set of mathematical functions. However, the right side of the schematic, a new situation of objects mapped is linearly separable.

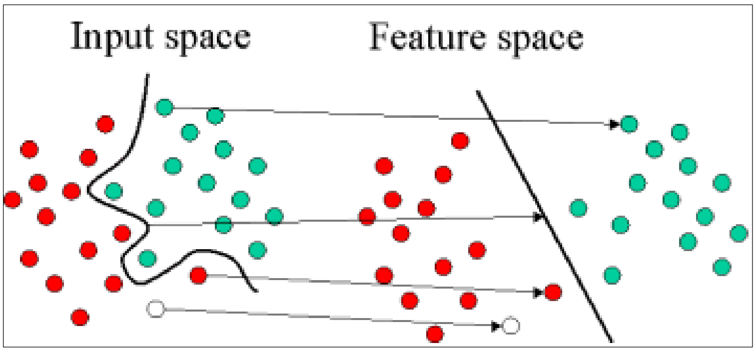


Figure 4: Example of Support Vector Machines (Statsoft, 2015)

1.3.6 Kalman Filter Technique

Kalman Filters, also known as Linear Quadratic Estimator (LQE) is an algorithm that provides a series of measurements containing noise (random variants) and inaccurate data, and produces a statistically optimal estimate of unknown variables based on efficient computation to minimize the mean square error. In addition, kalman filter is a commonly applied concept in time series analysis and it has several applications in technology such as signal processing, navigation, econometrics and control of vehicles, and many other applications in the field aircraft and spacecraft (Bhatt et al., 2014).

1.3.7 Hybrid Models or Composite Forecasts

Donkor et al. (2012) defined that this models are combination of methods and/or models to attain a composite forecast. Thus, the following expression is used when combining various models to achieve a composite forecast:

$$\hat{Y}_t = \beta_0 + \sum_{i=1}^{n} \beta_i \hat{Y}_{i,t} \qquad \text{(Eq. 3)}$$

Where:

$\hat{Y}_{i,t}$ = Predicted value of the time series at time *t* using the i^{th} model.

β_i = Coefficients are determined by optimization or least squares regression.

β_0 = Model intercept (or constant)

1.4 Organization of the Contents

This thesis describes my research work on analyzing and optimizing future water consumption in Al-Ain city. This thesis consists of nine chapters. The first chapter gives a general overview about the need of water resources, importance of water demand forecasting and the aim of this thesis. Also, it provides a comparative study among several modeling approaches in water demand forecasting such as time series analysis, regression analysis, artificial neural network, hybrid model, fuzzy logic, support vector machine, and kalman filters. Chapter two reviews the previous case studies from different regions in the world related to short term, medium term and long term water demand forecasting. Chapter three gives a brief description of the software IWR-MAIN that will be used in this study to predict water demand. In addition, this chapter provides information about the main variables and data required to build a model and also it provides previous studies related to this software. Chapter four presents information about the study area of Al-Ain city and also describes the Al-Ain 2030 plan. Also, several data (water quantity, population size and temperature values) are presented from different government departments and the best data will be selected. Furthermore, chapter five provides IWR-MAIN calibration and verification models. Additionally, two models from the IWR-MAIN suite were selected in this study; the constant use rate model and the linear forecasting model. Water demand forecasting scenarios are presented and discussed in chapter six. Moreover, water budget model of Al-Ain city is described in chapter seven. Finally, chapter eight concludes the results and gives some recommendation to be taken for water planning and management in the future of Al-Ain city.

Chapter 2: Literature Review

According to some previous researches, this chapter contains several forecasting methods of water demand such as artificial neural networks (ANN), time series, regression, fuzzy algorithm, intelligent forecasters construction set (IFCS), support vector machines (SVM), and hybrid model which makes a combination between different models.

Generally, Gulf Cooperation Council (GCC) countries which are Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the UAE have a shortage of freshwater resources that handicap the sustainable development in these arid countries. The characteristic of Arabian Peninsula is lack of freshwater resources due to absent in surface water resources and predominantly nonrenewable groundwater resources. Actually, the quality of the water in GCC countries is retrograde, on the other hand, reduction in the annual rainfall and growth in the population over the last few decades. This paper discussed the significance of water in the GCC countries and defined the water demand prediction in these six countries. Also, Al-Rashed and Sherif (2000) discussed that the oil and gas were the base of the economic development in GCC countries. The quick improvement in agricultural and industrial activities over the last few years has created further demand of water. However, the desalination plant was constructing as source of freshwater demand, but it is costly and its use is limited for drinking.

Essentially, the domestic and industrial demands depend on desalination water, whereas, 88% of the total water consumption in the GCC countries for agricultural demand depends on groundwater resources. As results, the study showed that the UAE had a high per capita consumption (over 700 L/day). In year 1990, Saudi Arabia had the highest total water consumption which contains domestic, industrial and agricultural demands (16.30 BCM), followed by UAE (1.49 BCM) and Oman (1.24 BCM). Obviously, the agricultural demand had the highest value in 1990 and also, the agricultural demand prediction increased over the years 2000 and 2010. Moreover, by the years 2000 and 2010, the domestic and industrial demands in the Saudi Arabia were assigned to be 2.90 and 3.60 BCM, respectively. In addition, Saudi Arabia had an irrigation demand reached to 20.21 BCM in 2000 and 21.70 BCM in 2010. Furthermore, at the same years, the domestic and industrial demands in the UAE were assigned to be 0.83 and 0.91 BCM, respectively. Additionally, by the years 2000 and 2010, the domestic and industrial demands in the Oman were assigned to be 0.20 and 0.27 BCM, respectively. Also, it had an irrigation demand reached to 1.25 BCM in year 2000 and 1.42 BCM in year 2010.

So, water policies and conservation techniques plus wastewater treatment, surface water harvesting and artificial recharge of groundwater should be adjusted at a larger scale. Whereas, the government and research institutes should assign great efforts to connect between water demands and water availability. Furthermore Al-Zubari (1998) mentioned that if future plans will increase the percentage of treated wastewater around 50% of domestic water supplies, the GCC countries have a chance to meet more than 11% of total water demands, and more than 14% of agricultural demands. Also, they have a plan to minimize groundwater withdrawal by more than 15% by the year 2020.

Carragher et al. (2012) developed the influence degree of household water stock (i.e. taps, shower heads, clothes washers and toilets). This study utilized data from the South East Queensland Residential End Use Study (SEQREUS) of 191 households to produce average day (AD) diurnal demand patterns. AD diurnal demand patterns per capita water demand for each cluster category (household occupancies, family types, and family income) were developed. AD hourly diurnal water demand depend on household efficiency clusters. Cluster households were determined to develop water stock efficiency star rating classification method based on weighted household. The study also aimed to describe the effects of the changes in AD peak hour demand to establish the efficient pipe network and capital infrastructure. The study results demonstrated that the residential water end use attained higher household water stock which reduced water demand by up to almost 25%. On the other hand, the AD peak hour had lower efficiency with stock of a higher star rating classification method. Furthermore, the study provided experimental evidence of household water stock retrofit programs to minimize the critical peak water demand values in future based on network modeling design. So, it makes delay in urgent upgrading requirement in water service infrastructure.

2.1 Artificial Neural Networks (ANN)

Ajbar and Ali (2013) developed a neural network model for annual and monthly water demand forecasting for the city of Mecca (Saudi Arabia). In addition, the study shed light on the effect of number of visitors to predict water demand. Neural network (NN) model was selected in this paper as this structure allows inputs with mixed time scales. Moreover, the study illustrated the challenges for forecasting water demand in an arid and oil rich country. No rivers or lakes found in that country, while its total renewable water resources is 95 m^3 per capita. However, the country which has water resources below than 1000 m^3 per capita, it is denote to water shortage. In addition, the study mentioned that a steady annual increment in the water demand. For these reasons, the kingdom is currently utilizing the desalination plants to gratify approximate half of the water demand which these desalination plants require high in cost and time. Consequently, the policy makers have a credible data in estimating the long term (annual) water demand to predict a suitable capital expenses in the development plans and to prevent any short-age in the domestic water supply. Correspondingly, short-term (monthly) water demand is significant for municipal authorities to improve the water production based on the effect of number of visitors on the total water consumption.

Bennett et al. (2013) utilized the ANN modeling technique to forecast a residential water end-use demand in Australia for the years from 2005 to 2008. Water end-use data established in the test for over 250 households, which includes demographic, socio-economic and water appliance stock efficiency information. On the other hand, three conventional ANNs were applied which were two feed-forward back propagation networks and one radial basis function network. As results, the databases which provided in ANN forecasting model were produced by the Hidden Layer Sigmoid Activation Linearly Activation Output (HLSALOA) network. Moreover, HLSALAO network was accomplished according to Error Back Propagation which it is able to provide accurately forecast water demand with highest R^2 (coefficient of determination) and least error. In addition, the water end-use demand forecasting model in this study had R^2 values of 0.33, 0.37, 0.60, 0.57, 0.57, 0.21 and 0.41 for toilet, tap, shower, clothes washer, dishwasher, bath and total internal demand, respectively. Moreover, the test results showed that the root mean standard errors (RMSEs) of forecasting models had less errors than the mean value in all cases (e.g. toilet, tap, shower, dishwasher, and total internal demand).

2.2 Time Series

A time series model was developed by Zhou et al. (2000) to forecast daily urban water demand for Melbourne, Australia in order to represent the effects of four factors on water use; i.e. seasonality, trend, auto-regression and climate regression. In daily water demand model, the consumption was divided into two components which were base (weather-insensitive) and seasonal (weather-sensitive) uses. Moreover, the base water use was predicted by the lowest months of water consumption. On the other hand, the seasonal water use was displayed by season, climate and persistence components. Thus, the test modeling was considered in the summer and winter six months separately and also in the case of summer period, it was divided into three separate ranges. In this study, the water use consumption was required to estimate along 24 hours when the water transfer from the head-water storage reservoirs to reach the consumers. Furthermore, the model utilized independent data developed with an Antecedent Precipitation Index (API) square root function for 62 days during summer period from December 01, 1996 to January 31, 1997. The paper concluded that amongst the seven models which measured and forecasted daily water consumption for the Metropolitan area, the model #7 showed the highest model efficiency of overall R^2 was 89.60%. In details for model #7, the R^2 of base and seasonal consumption was 46.40%, auto-regression (7.40%) and climate regression (35.80%).

Al mutaz et al. (2012) presents a probabilistic model for the forecast of future water demand for the city of Mecca in Saudi Arabia. The forecast of water demand in Saudi Arabia is significant because of its religious nature while the city attracts visitors all year long. Beside of that, Saudi Arabia has a shortage of its water supplies and it dependence on costly desalination plants to satisfy the water needs of its population. However, the study developed a forecast model under various variables; number of visitors, the household size (persons per house), the monthly mean of maximum daily temperature and the average household income for local population. This study was limited to a three year forecast period; from 2011 to 2013 time period in monthly increments. The forecast of demand is denoted by an interval within which 90% of potential demand would normally fall. The results of this study showed that the demographics are the limiting factors and are always subject to change. So, the number of Haj visitors is fully controlled. But, the authorities are arranged to additional growth in the coming years and the number of Umrah visitors, because these visitors can come any time during the year and normally stay longer. The main reason for this planning is the economic benefit expected from this large number of tourists. In addition, the study displayed that conservation measures are significant in reducing water demand. In 2013, the conservation in water demand reached 5%. On other hand, the study predicted that the long term (i.e. until 2030) conservation plan in water demand could attain a reduction of around 24%. Moreover, another implement for water management for long term is increasing in water tariffs. Actually, the authorities are not allowing for any rigorous water pricing policy, however, may change in future. Also, according to the change in policies related to demographic factors and the probable change in water pricing policy, it concluded that shorter term (i.e. 3 years) water demand forecast is more reliable and beneficial than any longer term forecast.

Cresswell and Naser (2014) developed a short term forecast model to predict a water demands for 24 hours. A time series model was utilized to forecast water demand for the urban and agricultural zone in the South East Kelowna Irrigation District (SEKID), Canada. The data used to forecast water demand of SEKID for the years 2005, 2006 and 2008 and the data confirmation was completed for the year 2010. For years 2007 and 2009, data were not utilized because the data were not accurate as water restrictions were placed on the consumers in these mentioned years. The model took into consideration the impacts of base, seasonal, climatic, and persistence components in demand prediction. However, the base demand was determined by utilizing the least value of demand in each month for all the years. On the other hand, a Fourier series approach was used to model seasonal demand in order to utilize the water demand over the course of a year. Moreover, climatic demand was described as temperature and precipitation and it was modeled using regression analysis. In addition, the persistence demand defined as the impact of previous day's demand on the current day's demand, thus it was also modeled using regression analysis. The study results showed that the calibrated model predictions for demand in the years 2005, 2006 and 2008 had R^2 of 82% in the comparison between measured data. Furthermore, the model validated with measured data for year 2010 and determined R^2 was 77%. Thus, the study concluded that the results had an acceptable level of precision in forecasting water demand.

2.3 Regression

The forecasting assumptions are most critical about the future values of explanatory variables. The study by Dziegielewski and Baumann (2011) described the techniques for developing a future water demand forecast which improved its acceptability by decision makers. To develop a credible forecast, first of all, it needs to obtain a historical data on water use. However, a beneficial forecasting model needs an accurate estimate of the regression coefficients for the clarifying variables. The size of the regression coefficients (i.e. price, income, air temperature, and precipitation) developed from the forecaster impartially for key explanatory variables. The second step to develop a credible forecast is to develop forecasting assumptions which are the main component of the forecast. In addition, the moment that the forecasted quantities of future water demand were organized, the post-forecast analysis of results should be prepared. The analysis means to identify and quantify the effects of individual forecasting assumptions on the final results. The post-forecast analysis certified that the forecast was accepted by decision makers.

The scenario of water demands forecasting results in the 11 County planning areas in Northeastern Illinois showed the possibility of extremely increase in total water withdrawals by 2050. Two scenarios were formulated to denote growth assumptions; current trends (baseline scenario) and more resource-intensive (high-growth scenario). In year 2050, total withdrawals under baseline scenario would increase by 2.41 MCM/day and under high-growth scenario could increase by 4.31 MCM/day. However, these additional demands need large capital expenses for water infrastructure and probably have significant impacts on some of the regional sources of water supply that could generate increase demands on water from Lake Michigan.

Lowry et al. (2011) presented an approach to estimate residential irrigation water demand for a large landscape scale in an urban environment of years 2010 to 2050. An essential purpose in this study is explaining how a growth of an urban forest has affects in overall irrigation water demand of a semi-arid urban area. The objectives in this study focused into two points. The first objective was to predict residential landscape water demand of various residential landscapes types; based on different factors such as water-loss rate (i.e. plant factors) and distribution uniformity (DU) factor. The second objective was to estimate upcoming residential landscape water demands of the growing urban forest. To apply water demand model in forest area, spatial regression models were utilized to estimate the upcoming areal extent of tree canopy and exposed turf grass.

The study indicated the prediction of irrigation water demand for 542 residential neighborhoods in USA. The results showed that the areal extent of irrigated landscapes recommended high amount of irrigation water demand. However, irrigation water demand may decrease when increase urban forest plentiful overtime within a specific area. In addition, according to first objective, study determined that water-loss coefficients present in crop plants are lack in landscape plants. A vital idea in water-loss coefficient or plant factor (PF) is extremely used for landscape management recommended in urban areas which needs extra reliable coefficients for trees and woody plants. Moreover, the second factor in irrigation water demand model is distribution uniformity (DU) factor. Low DU is very important for irrigation to excess in uniform turf grass landscapes which they do not need uniform water application. On other hand, simultaneous autoregression (SAR) models utilized to estimate the upcoming areal extent of tree canopy and exposed turf grass. The SAR model expected that when an urban tree canopy increases, exposed turf grass decreases based on net effect of an incommodious decrease in residential landscape water demand. So, according to this, comparative differences show in water lost through evapotranspiration by various landscape types.

2.4 Fuzzy Algorithm

The concept of fuzzy algorithm is to express non-linear relations among variables. In the study of Petrovic et al. (2014), fuzzy algorithm was utilized to forecast the water leakage of the leading UK water supply company. Three techniques were involved in this study; Takagi-Sugeno (eTS) algorithm, fuzzy clustering method and statistical forecasting methods. Five years real-world data (2006–2011) provided by the company is used to solve a leakage forecasting problem by various techniques which mentioned before.

The results of this study presented that fuzzy eTS algorithm attained best results for testing data than other fuzzy clustering algorithms and statistical methods. Moreover, same results were achieved when comparing with cluster radii. However, the algorithm produces a smaller number of clusters than standard statistical forecasting methods that indicates to more obvious forecasting models.

2.5 Intelligent Forecasters Construction Set (IFCS)

Lertpalangsunti et al. (1999) described a set of tools for construction of hybrid intelligent forecasting system which it was utilized for water demand prediction in the City of Regina's water distribution system and Environment Canada. Intelligent Forecasters Construction Set (IFCS) was supported multiple forecasting models such as fuzzy logic (FL), artificial neural networks (ANNs), knowledge-based and case-based reasoning (CBR). However, IFCS system supplied an application improvement environment for constructing hybrid intelligent forecasters. Moreover, several programming can be implemented for instance; visual programming, production rule inference and procedural programming. The IFCS system was beneficial for enhancing operation costs of water plants which some of them require to pay a flat rate for electricity that depending on peak kilowatt demand. Thus, the costs of the plant can be reduced if the peak kilowatt demand can be minimized.

As results from this technique, the accuracy of IFCS prediction system influenced by the quality of the data sets. In general, the Mean Absolute Percentage Error (MAPE) of the water demand prediction was higher than comparing with the power demand prediction. This related to that the data based on water demand are noisy, but the data based on electricity demand were relatively noise free. Also, the study concluded that the multiple modules of forecasting gives better results than those which using single forecasting models. Whereas, the MAPE was 3.88%, 6.11% and 7.54% from the multiple ANNs model, the linear regression (LR) model and the CBR, respectively.

2.6 Hybrid Model

2.6.1 Artificial Neural Networks (ANN) and Support Vector Machines (SVM)

The main purpose of the study carried by Msiza et al. (2007) to compare between two mechanisms to forecast both short-term and long-term water demands which are Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs). This study was concentrated on water demand forecast in South Africa’s Gauteng Province. The first technique was ANN that captured two architectures which were multi-layer perceptron (MLP) and the radial basis function (RBF). Then, they compared to establish the Artificial Neural Genius (ANG). However, the second technique was SVM which involved the various models with different degrees and scales. These models compared to establish the Support Vector Genius (SVG).

Moreover, these two geniuses had a comparison to define the overall genius (OG) is the generalization ability of the two geniuses.

As a result, the ANG had 2.96% error and 100% accuracy. On the other hand, SVG had 5.47% error and 100% accuracy. Obviously from this study that ANG had better generalization ability than SVG. So, ANNs technique obtains better performance than SVMs technique.

2.6.2 Neural Networks (CNN), Fuzzy Logic and Genetic Algorithms

Pulido-Calvo and Gutiérrez-Estrada (2009) predicted irrigation water demand using a hybrid model which was also applied with Computational Neural Networks (CNNs), fuzzy logic and genetic algorithms. First of all, the test was modeled by the univariate autoregressive neural network, and then model forecasting was corrected the by the fuzzy logic technique whose parameters were modified using a genetic algorithm so as to develop the forecasting accuracy. Moreover, the model data was obtained from the Fuente Palmera irrigation district situated in Andalucía, southern Spain to forecast daily water demand one-day ahead. Actually, daily measured demand data were taken from years 1988, 1989, 1990 and 1991.

The results showed that the hybrid model had the best results in accuracy and errors compared with univariate and multivariate autoregressive CNNs. Furthermore, the accuracy value of hybrid model was 89% and the error was less than 21% that equals to 20.27%. On the other hand, hybrid model confirmed that it was a robust tool which did not require huge data and it was appropriate for the improvement of policies on irrigation water consumption. This model helps to reduce operation costs of water supply systems in southern Spain.

2.6.3 Neural Network Model with Genetic Algorithms

Kim et al. (2001) presented the daily water demand forecasting for the city of Seoul, South Korea by utilizing the neural network model and genetic algorithms. The temperature and daily water data recorded for five years from January 1992 to December 1996. However, the first four years data collected which utilized for training of model and the last one year data collected which utilized for testing.

A neuro-genetic model in this study used variables for testing as input. The input parameters that used were two days previous of water demand and today's and yesterday’s average temperatures. In addition, the results of this study described that the best parameter showed in neuro-genetic model is today's water demand forecasting.

2.6.4 Kalman Filter (EKF) and Genetic Programming (GP)

Nasseri et al. (2011) developed a hybrid model for forecasting monthly water demand utilized Extended Kalman Filter (EKF) and Genetic Programming (GP) in Tehran, the capital of Iran for the years from 1992 to 2002. The Extended Kalman Filter was applied to derive latent variables so as to make a water demand forecasting based on GP results.

There were five formulas presented according to results of Genetic Programming, on the other hand, the first five to three lags of observed water demand were used as independent inputs. However, each input was measured mathematically for each model results. Moreover, this study also mentioned that a model that had compatibility of the computed water demand versus the observed water demand was utilized for forecasting depending on EKF technique. In addition, the model results showed a visible effect on observed water demand forecasting. Thus, this study results can help to those who concern about minimizing the hazards of urban water demand forecasting

2.6.5 ANN, PPR, SVR, MARS and Random Forests

Several models were utilized to predict hourly urban water demand in a city in south-eastern Spain (Herrera et al., 2010). Basically, these models were obtained using time series data which detailed water demand in a hydraulic sector in the city. Moreover, the forecasting models were artificial neural networks (ANN), projection pursuit regression (PPR), support vector regression (SVR), multivariate adaptive regression splines (MARS) and random forests. However, simple model was also assigned in this study depended on the weighted demand data resulting from the experimental analysis of the predicting data.

The main purpose of using several forecasting modeling was to select the best model to obtain forecasting for urban water demand in a city in south-eastern Spain. The results showed that the models based on time series data confirmed more accuracy than weighted pattern-based model. Moreover, support vector regression (SVR) had the most prediction performance compared with other models, closely followed by PPR, MARS Random Forests. In addition, the study results described that the artificial neural networks (ANN) model had an unsatisfactory prediction performance. Furthermore, when used EPANET calibrated model and compared with the modeling results, it shown that the both results were clearly met.

2.7 Water Budget Model for Al-Ain City

Ito et al. (2009) revealed a model to consider a lake water budget, and Lake Ikeda in Japan was taken as the study area. Darcy's law and tank model was utilized for inflow from the Lake catchment area and leakage from the lake bottom. Also, the shuffled complex evolution method was adjusted for model parameters. Moreover, the estimated monthly lake evaporation rate and calculated time series of daily lake levels were analyzed in this study. The results recommended that a large decline in the lake level will occur in case agricultural water use and drinking water use are pumped from the lake while river water is supplied to the lake. On other hand, the decline will not occur when lake water is used for drinking water only, even though without river water supply. Consequently, the study determined that river water supply play a vital role in the water management and it recompenses for the decrease in lake water. Sustainability of the Lake Ikeda will require suitable use of simulation models, developments in agricultural water management, and considerate lake management issues among residents and other stakeholders.

Mohamed and Al-Mualla (2010) utilized a hydrological budget model to estimate the groundwater recharge in Al-Ain region of UAE in the year 2012. Al-Ain is the second largest city in the Emirate of Abu Dhabi and the third in the UAE. The study presented several components of a water budget model which model inflows such as precipitation, recharge from treated sewage effluents ponds, surface flow, irrigation returns, and subsurface inflow. However, the model outflows such as evapotranspiration and subsurface outflow. The surficial unconfined aquifer in the eastern part of the Abu Dhabi Emirate was selected in this model. The study results showed that the input flow is almost double the output flow. So, the recent groundwater rises in different areas in Al Ain. Consequently, this study explained that the differences might be caused by different sources for example; the use of drinking water in irrigation in some farms. Another reason might be the leakage from the water distribution network.

Integrated water resource management (IWRM) and the water conservation was analyzed by Gao et al. (2014). Several objectives in this study were implemented to improve IWRM, which considered the decrease of freshwater demand and the decrease of total water supply cost. However, the Tianjin was taken as the study area. The study results shown that agriculture sector had the largest preference for saving water, while the public sector had the weakest preference for saving water. In case of developing the water transportation method, the agriculture sector can attain 62.10% of the total water savings. The optimization of the IWRM revealed that the freshwater savings would be 21.50%, and also the total water supply cost would reduce by 13%. Moreover, the study noticed that the changing in water savings amount had an effect of water pricing so, the water price was recommended to increase between 1.5–1.7 times the original price.

Petru et al. (2014) utilized a water balance model to compute water budgets of a mitigation wetland, and Piedmont region of Virginia was taken as the case study. The model calibration data was analyzed during the 17 month monitoring period along with precipitation, temperature, soil physical properties, and estimated site characteristics. Two areas were conducted in this study, one disturbed area and the other non-disturbed area, by construction practices usually implemented for a mitigation wetland created in the region. In addition, another model was conducted to represent the disturbed boundary conditions of wetland design. Also, it represented the substituted soil data observed at the non-disturbed study area. The study displayed that disorder to key soil properties will need surface storage to attain jurisdictional hydrology, and that construction practices can perform in longer durations of ponding during the growing season, therefore possibly changing the habitat type for the wetland from what was originally designed.

Wang et al. (2014) observed the water budget variables and closure for sixteen large Canadian drainage basins. The utilized datasets involve two precipitation grids, land surface evapotranspiration and water surface evaporation, streamflow measured at hydrometric stations, and total water storage change derived from satellite observations. The monthly water imbalance was shown as 30% on average of the corresponding monthly precipitation. The water budget imbalance obtained for years 2002 to 2008 varied from nearly 0 to ±10 mm/month. The positive and negative water budget imbalances of sixteen basins were largely offset and the all basin imbalance was very nearly zero. All uncertainties in precipitation, streamflow, evapotranspiration and total water storage change were participated to the water budget imbalance and their relative quantities were found to differ with basin and season. Generally, precipitation presented the highest uncertainties which had similar magnitudes to the water budget imbalances. On other hand, the study results determined that the water imbalance gained for some basins is relatively large, therefore the study recommended that the improvements in both the observation networks and models are essential before the water budget closure can be considerably improved over the region.

Chapter 3: IWR-MAIN Software

3.1 History

Water utilities face multiple financial challenges in order to maintain existing and future water supplies as well as need for increased investments in water supply infrastructure. There are substantial opportunities to save capital investments at water in the long term by understanding and managing water use. In this case, one of the best saving strategies is to minimize the error estimates in predicting water demand.

IWR-MAIN software was designed to provide flexible tools for estimating and forecasting municipal water requirements. Initially, during the 1960's, some researchers started working on IWR-MAIN system for the residential and commercial water use research projects at Johns Hopkins University, and also for the U.S. Office of Water Resources Research. However, the original system was called MAIN, and then it was development in MAIN II. These early analytical tools were based on different researchers such as Howe and Linaweaver (1967) and Wolff et al. (Consortium for Atlantic Regional Assessment "CARA", 2015). On the other hand, the initial system was developed by Hittman Associates, Inc., in 1968 regarding to municipal and industrial needs. In year 1982, the MAIN system was improved by U.S. Army Corps of Engineers' Institute for Water Resources and changed its name to IWR-MAIN Water Use Forecasting System (Tri-State Water Resource Coalition, 2015).

Eventually, a PC version was created and the computation techniques were incorporated into the new model based on researches and available data which then the software distributed by the Corps of version 5.1 in 1987. With the release of version 6.0 in 1994, this was accomplished by Planning and Management Consultants, Ltd. (PMCL, now CDM Smith) under the sponsorship of the Institute for Water Resources and U.S. Army Corps of Engineers. Moreover, PMCL released a new version of IWR-MAIN software in 1999 which is Windows Version. Also, in the 1990s and 2000s, the software was used widely for forecast studies for a number of major water utilities in the U.S. In 2003, PMCL was developed by CDM Smith (IWR-MAIN Water Demand Management Suite, 2015). Until now, IWR-MAIN software using in several water utilities such as Indianapolis Water Company; the City of San Diego Water Utilities Department; Phoenix Water and Wastewater Department; Southwest Florida Water Management District; Metropolitan Water District of Southern California and El Paso Water Utility (Consortium for Atlantic Regional Assessment “CARA”, 2015).

3.2 Data Management

The IWR-MAIN software consists of two main managers; Forecast Manager and Conservation Manager. The first manager which is ‘Forecast Manager’ is used to estimate urban water use into the future. On the other hand, ‘Conservation Manager’ is utilized to compute water saving by reducing water consumption in specific end uses (California Department of Water Resources (CDWR), 2015).

3.2.1 Forecast Manager

The Forecast Manager has been developed to help water managers in their planning to predict long term water use by various sectors/subsectors of water use and by time (annually, seasonally, and monthly).

The purposes of Forecast Manager are to use demographic, housing, and other available statistic to estimate existing and future per unit water demands and to use prediction of population, housing, etc. to derive baseline forecasts of water use.

Davis et al. (1987) illustrated the IWR-MAIN software forecasting options and the organization of the IWR-MAIN system by various sectors as shown in Figure 5 and Table 1.

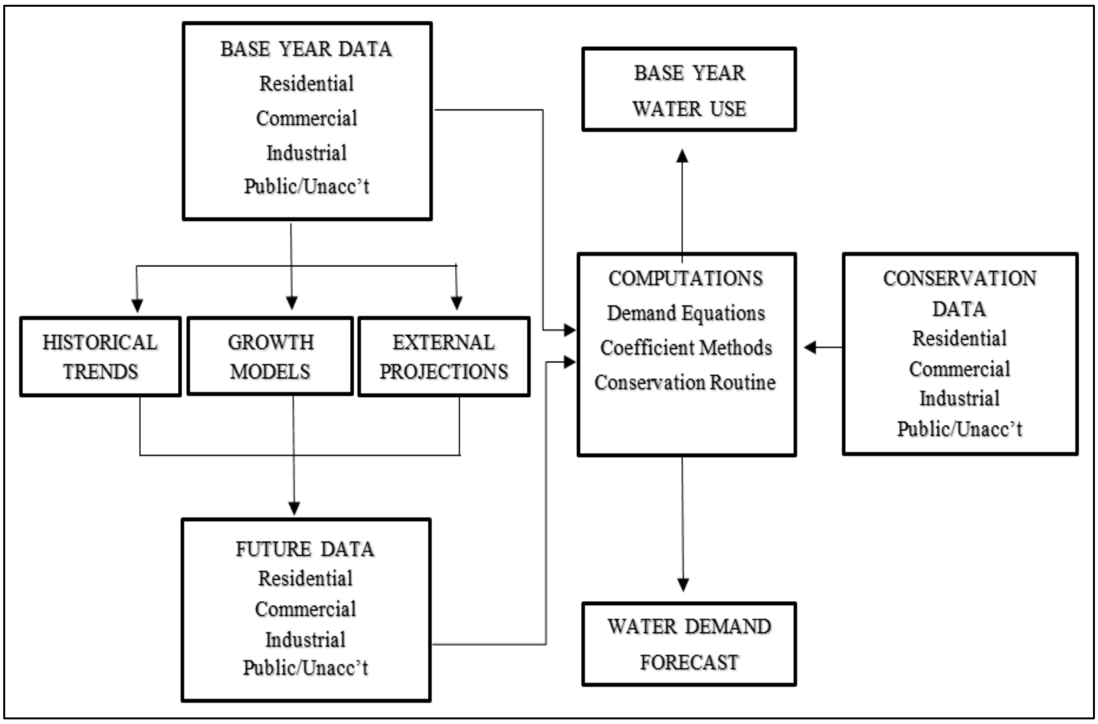


Figure 5: IWR-MAIN system and forecasting options (Davis et al., 1987)

Table 1: Organization of the IWR-MAIN system (Davis et al., 1987)

Sector	Water Use Category	Forecast Method
Residential	Metered and sewered residences	Econometric demand models
	Flat rate and sewered residences	Multiple coefficient requirements models
	Flat rate and unsewered residences	Multiple coefficient requirements models
	Master-metered apartments	Multiple coefficient requirements models
Commercial/ Institutional	Up to 50 user categories, including 23 categories defined as groups of four-digit SIC codes	Unit use coefficients (per employee)
Industrial	Up to 200 user categories, including 198 manufacturing categories defined by three-digit and four-digit SIC codes	Unit use coefficients (per employee)
Public/ Unaccounted	Up to 30 user categories, such as distribution system losses and free service	Unit use coefficients or per capita requirements

3.2.2 Conservation Manager

The Conservation Manager is designed to compute water saving by reducing the average per unit water consumption of specific end uses. Moreover, the Benefit-Cost Tool within the IWR-MAIN Conservation Manager allows the user to run the benefit-cost procedures to see which program alternative is economically viable to choose. The main features and capabilities of IWR-MAIN software is to estimate the effectiveness of water conservation, allows user to evaluate forecast long term water saving of various conservation practices, allow the user to evaluate and compare economic metrics of conservation program benefits and allow the user to generate reports and provide graphics of conservation results.

3.3 Forecasting Models

IWR-MAIN provides four water use forecasting methods for each sector/subsector which are Constant Use Rate, Build Forecasting Model, Specify Forecasting Multiplicative Model, and Specify Forecasting Linear Model, as shown in Figure 6 below.

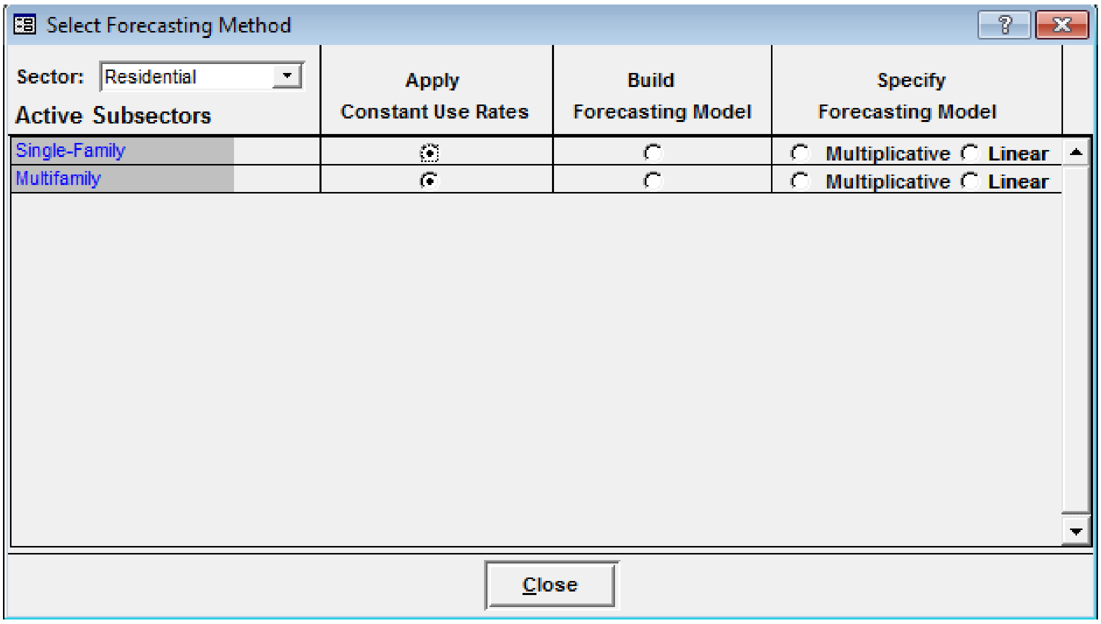


Figure 6: Four main water use forecasting methods

3.3.1 Constant Use Rates Model

In this model, the base year per unit water use rate (q) is calculated from the base year water use and the number of counting units (N) for each sector. Consequently, this rate of use is held constant for each subsector for all the forecast years, then it is multiplied by the forecasted counting units to generate the forecasted water use for each sector. However, with this method, the change in the water use forecast from year to year depends only on the change in counting unit (N). Therefore, the quantity of water use is calculated as:

$$Q_{s,m,y} = N_{s,m,y} \cdot q_{s,m,b} \cdot d \qquad \text{(Eq. 4)}$$

Where:

Q = Gallons of water used in subsector (s) in month (m) in year (y)

N = Number of unit in subsector (s) in month (m) in year (y)

q = Average daily use rate per unit in subsector (s) in month (m) in base year (b)

d = Number of days in month (m)

3.3.2 Build Forecasting Model

This method calculates the base year per unit water use (q) by the base year water use and number of counting units for the subsector, as follows:

$$Q_{s,m,y} = N_{s,m,y} \cdot q_{s,m,b} \cdot \left(\frac{X_{j,s,m,y}}{X_{j,s,m,b}}\right)^{\beta_{j,s,m}} \cdot d_m \qquad \text{(Eq. 5)}$$

Where:

Q = Gallons of water used in subsector (s) in month (m) in year (y)

N = Number of unit in subsector (s) in month (m) in year (y)

q = Average daily use rate per unit in subsector (s) in month (m) in base year (b)

X_b = Value of explanatory variable (j) in base year (b)

X_y = Value of explanatory variable (j) in year (y)

β = Elasticity of per unit use for variable (j) in subsector (s) in month (m)

d = Number of days in month (m)

The explanatory variable are specified by the user and its value may change over time. Moreover, the change in the water use forecast from year to year is clarified by the change in the explanatory variable in addition to the change in counting unit.

3.3.3 Specify Forecasting Model

3.3.3.1 Multiplicative

This forecasting method estimates the future subsector water use as a function of a constant times a set of explanatory variables. In addition, the user should have a model developed prior to using this software. The Forecasting Multiplicative Model is calculated as:

$$q_{s,m,y} = e^{\alpha_{s,m}} \cdot \prod_j X_{j,s,m,y}^{\beta_{j,s,m}} \qquad \text{(Eq. 6)}$$

Where:

q = Estimated daily use rate per unit in subsector (s) in month (m) in base year (y)

α = Model constant (intercept of model that is linear in log form) in subsector (s) in month (m)

e = Base of the natural logarithm

X_y = Value of explanatory variable (j) in year (y)

X = Value of explanatory variable (j) in subsector (s) in month (m) in year (y)

β = Elasticity of per unit use for variable (j) in subsector (s) in month (m)

The most important in this model is the user should avoid having variable with zero values so, the user should enter (+1) instead of any variable has a zero value. Additionally, the estimated daily use rate per unit (q) is then multiplied by the number of units and the number of days in the month, as follows:

$$Q_{s,m,y} = N_{s,m,y} \cdot q_{s,m,y} \cdot d_m \qquad \text{(Eq. 7)}$$

Where:

Q = Gallons of water used in sector (s) in month (m) in year (y)

N = Number of unit in subsector (s) in month (m) in year (y)

q = Average daily use rate per unit in subsector (s) in month (m) in base year (b)

d = Number of days in month (m)

3.3.3.2 Linear

This forecasting method estimates the future subsector water use as a function of model intercept plus the explanatory variables. In addition, the user should have a model developed prior to using this software. The Forecasting Linear Model is calculated as:

$$q_{s,m,y} = \alpha_{s,m} + \sum_j \beta_{j,s,m} X_{j,s,m,y} \quad \text{(Eq. 8)}$$

Where:

q = Estimated daily use rate per unit in subsector (s) in month (m) in base year (y)

α = Model intercept for subsector (s) in month (m)

X = Value of explanatory variable (j) in subsector (s) in month (m)

β = Coefficient of per unit use for variable (j) in subsector (s) in month (m)

Then, the estimated gallons per unit per day for the month (q) is multiplied by the number of units (N) and by the number of days in month, as follows:

$$Q_{s,m,y} = N_{s,m,y} \cdot q_{s,m,y} \cdot d_m \quad \text{(Eq. 9)}$$

Where:

Q = Gallons of water used in sector (s) in month (m) in year (y)

N = Number of unit in subsector (s) in month (m) in year (y)

q = Average daily use rate per unit in subsector (s) in month (m) in base year (b)

d = Number of days in month (m)

Furthermore, the change in the water use forecast from year to year is clarified by the change in the explanatory variable in addition to the change in counting unit.

3.4 IWR-MAIN Case Studies

The authors “Mohamed and Al-Mualla” (2010) published two papers about the water demand forecasting in Umm Al-Quwain (UAQ) Emirate, sited in the northern part of UAE, until year 2030. The first published paper was about water demand forecasting using the constant rate model, and the another paper was about water demand forecasting using the IWR-MAIN specify forecasting model. For more details, the explanation of two papers is shown below.

The first published paper was about the constant rate model which was used to forecast water demand in UAQ (Mohamed and Al-Mualla, 2010). There were two water consumption databases were used in this study in addition to population size. The first database determined average daily water use from years 1980 to 2000. However, the second database determined actual measured water consumptions from years 2001 to 2008. While, the model calibration showed that year 2000 and 2002 were used as base years for both databases. The study results expected that the water needs in UAQ in 2020 will be required more than 50% increase in the current water demand and double of the current demand will be needed before 2030. Also, the study results indicated that database two provided higher calibration error than database one. In addition, model calibration suggested that the year 2000 was the best base year from database one. On other hand, the year 2002 was the best base year from database two. The forecasted metered demand of database one will reach around 20,000 m^3/day and 30,000 m^3/day in years 2014 and 2030, respectively.

Furthermore, for database two, the predicted average daily demand will reach around 12,000 m^3/d and 19,000 m^3/d in 2014 and 2030, respectively. Based on the estimated average absolute relative error (AARE), a weighted average for the both base years (2000 and 2002) of the both databases is intended as 17,300 m^3/d and 25,900 m^3/d for the years 2014 and 2030, respectively. Nowadays, water consumption in UAQ Emirate is decided without any price impact. Application of water pricing mechanisms is greatly needed to mitigate unnecessary building desalination plants. Moreover, completion of meters installation in all facilities in the Emirate is estimated to decrease future water demand.

The second published paper was about the IWR-MAIN specify forecasting model which was used to forecast water demand in UAQ Emirate (Mohamed and Al-Mualla, 2010). There were two databases used in this study; the first database determined average yearly water consumption since years 1980. However, the second database determined monthly water consumptions from years 2000. In both databases, there were several variables provided in this study; water consumption and three independent variables which were population, average temperature and average rainfall. The study showed that only the population size has an effect with water consumption in UAQ. Additionally, both databases were divided into two periods; regression period (started with the first year of each database and ended at the base year) and calibration period (started with the base year and ended in 2007 in both databases). Over the regression period, the software ‘Statistical Package for the Social Science’ (SPSS) was used to find the values of intercepts and coefficients between the independent variables and actual water consumption. Then, over the calibration periods, these intercepts and coefficients were used in IWR-MAIN to find the values of water demand. As results, the study expected that the water needs in UAQ in 2015 will be required more than 50% increase in the current water demand and double of the current demand will be needed before 2025. The study results indicated that database two provided higher calibration error than database one. In addition, four scenarios of water demand forecasting were implemented. In first scenario, the results displayed expected increase in water demand due to population increase, while the results of second scenario displayed expected increase in water demand due to the effect of average annual income, as a further independent variable. In scenario 3, the losses (unaccounted) water demand and unmetered water demand were taken into consideration. The unmetered water demand is almost equal to metered water demand in UAQ Emirate, however, it must be taken into consideration in the future prediction before meters are installed in all emirates' facilities. In fact, based on this study, UAQ Emirate implemented restrictions in water use and conservation to save produced water and reduce losses. Moreover, scenario 4, depending on the data provided in this study, the annual water demand increased four times than predicted in scenario 1. So, in this case, construction of new desalination plants will be required to cover this enormous increase in water demand.

Some advantages of IWR-MAIN program were determined by Boland (2011) such as it is highly disaggregated by user for as many as 284 different water use categories. Also, it can forecast water with separate political jurisdiction, with different tariffs and different water conservation polices. Moreover, IWR-MAIN forecasting model may incorporate with several categories/sectors water use and interactive to changes in any of these sectors. Furthermore, IWR-MAIN water forecasts are seasonally disaggregate so, this provide an ability to estimate changes in peak period water use and to establish adequacy of water supply. Additionally, it takes into consideration the long-term existing or future water forecasts as many as eighteen water conservation.

Donkor et al. (2014) mentioned that the regression models is determined by several research studies to set the level of demand for long-term forecasts given specific scenarios. This approach is used to predict future demand by a limited number of discrete combinations of the independent variables. The goal of using regression model is to determine the impact of future water demand in different scenarios of the determinants. IWR-MAIN is developed by the U.S. Army Corps of Engineers' Institute for Water Resources, and Demand-Side Management Least-Cost Planning Decision Support System (DSS) and it is created to forecast water for specific area by different sectors.

Chapter 4: Study Area

4.1 United Arab Emirates

The United Arab Emirates (UAE) is situated in the middle of the Arabian Gulf, north of the equator. It is located between latitudes 22 degrees and 26.30 degrees to the north, and longitudes 51 degrees and 56.30 degrees to the east. It is bordered from the north by the Arabian Gulf. However, UAE is bordered from the south by the Sultanate of Oman and the Kingdom of Saudi Arabia. Also, from the east by the Gulf of Oman, and from the west by the State of Qatar and the Kingdom of Saudi Arabia. In addition, the total area of the UAE country is 83,600 km^2, plus the area of archipelago which is about 5,900 km^2 (Rizk and Alsharhan, 2003).

The UAE is composed of seven emirates which are Abu Dhabi (is the capital of the state), Dubai, Sharjah, Ajman, Umm Al-Quwain, Ras Al-Khaimah and Fujairah. The union of seven emirates was established on second of December 1971. The U.A.E since its establishment has an economic development which is hard to achieve even in the most developed communities. The U.A.E has rapidly developing in social and physical based on its enormous oil proceeds providing the basic requirements of society.

The UAE lies in the arid tropical zone that extending across Asia and North Africa. Whereas, the U.A.E country lies on the coastal zone of both the Arabian Gulf and the Gulf of Oman, it has an effect of climatic conditions from Indian Ocean. As a result, the temperature in summer always escorting the high humidity.

The U.A.E country is obtained one of the world best winter resorts. The climate condition between the months of November and March is described as a moderate warm climate prevails throughout the day (average temperature of 26 degrees Celsius) while, a lightly cool climate prevails during the night (average temperature of 15 degrees Celsius). Moreover, the humidity between the months of June and August tends to get higher values.

In addition, the winds in the U.A.E country tend to change between southern or south easterly, western or northern and north westerly. Rainfall is comparatively little and the annual average rainfall does not exceed 6.5 cm. However, the rainfall occurs throughout the months of November to April. On other hand, more than half of the rainfall takes place during the months of December and January (MyWeather2, 2014).

4.2 Al-Ain City

Al-Ain city is the fourth largest city in the UAE which is known also as the "Garden City of the Gulf". It has a very fertile land, rich in greenery and abundance of farms and public parks. Al Ain city is also rich in groundwater plus several artesian wells.

Al-Ain city is situated about 160 km east of the capital of Abu Dhabi, about 120 km south of Dubai and it is located on the border with the Sultanate of Oman (Figure 7). It covers an area around 13,100 km^2 with a population of 690,932 in year 2013 (Al Ain Distribution Company (AADC), 2014). On other hand, as you travel to the east, the topography of Al Ain city is unique and differs. The most famous feature in

Al Ain city is Hafeet Mountain which is lying to the southeast and its height is 1,249 meters.

Figure 7: Location map of Al Ain city (Google Map, 2014)

Al-Ain city has an arid climate and it has high temperatures over the course of the year. Usually, in winter season, the temperature varies from 10°C to 30°C and is rarely below 10°C. On other hand, in summer season, the temperatures can reach as high as 50°C.

Rainfall is irregular and it is falling generally in winter season (from November to March), also the city has an averages rainfall (100–120 mm) per year in most of the emirates. The mean annual rainfall in Al-Ain city is 96.40 mm while, the relative humidity is 60 % (Murad et al., 2012).

The relative humidity normally varieties from 13% which is very dry to 88% which is very humid over the course of the year. So, Al-Ain city has an advantage during the summer season, it has low humidity which is goal of many people at that time of year. In addition, generally in Al-Ain city, the wind speed is varying from 1 m/s to 8 m/s (light air to fresh breeze) over the course of the year (Weatherspark, 2014).

4.3 Al Ain City 2030 Plan

4.3.1 Vision

Al-Ain city is known as the oasis city of the UAE. However, it is located as a pivotal crossroads. Because of high population growth in addition to low density development, Abu-Dhabi Government and Al-Ain Municipality aim to develop Al-Ain city, and preserve the traditions and its restful lifestyle (Abu Dhabi Urban Planning Council (UPC), 2014).

On other hand, plan for Al-Ain city on 2030 is the vision of His Highness Sheikh Khalifa bin Zayed Al Nahyan, President of the United Arab Emirates, for the continued accomplishment by the late Sheikh Zayed bin Sultan Al Nahyan.

4.3.2 Development Objectives

The plan of Al-Ain 2030 presents a great future to enhance a sustainable development in various aspects such as an environmentally, economically, culturally and socially sustainable. However, to keep a balance between development and conservation, plan of Al-Ain 2030 will encourage the authentic Arabic identity whereas aid an improving a modern country (Abu Dhabi Urban Planning Council (UPC), 2014).

Oasis city had an old irrigation method known as falaj. On the other hand, the sustainability trends to keep groundwater resources and conserve natural habitats. Moreover, the future evolving of Al-Ain city includes a plan to improve the renewable water resources and minimize the consumption of non-renewable water resources (Abu Dhabi Council for Economic Development (ADCED), 2014).

4.3.3 Development Requirements

Environmental, cultural, social and economic developments are the main requirement of Al-Ain 2030. Al-Ain will be a healthy oasis city based on traditions of water management and also protect the natural environment. Moreover, cultural development of Al-Ain 2030 will include protection of cultural heritage that the plan recommends keeping on the existing housing character which is based on the ‘fareej’ model, low-rise and pedestrian-scaled construction. Thus, Al-Ain will protect and respect its heritage, its cultural landscapes and its historic assets. In addition, the social developments of Al-Ain in 2030 will preserve a high quality of life based on its traditional patterns of living, spaciousness, low-built scale and its public garden. Furthermore, the economic developments of Al-Ain in 2030 will include service trades, education and healthcare industries that the future development will support ecological and cultural tourism (Abu Dhabi Urban Planning Council (UPC), 2014).

4.3.4 Water Management

Environmental sustainability of Al-Ain city includes a suggestion to refill the reduction of aquifer level and keep protecting it from pollution. Also, the oasis in Al-Ain city will be conserved instantly by reintroduction of organic practices and the conventional vertical layered ecology of palms and trees. However, a commission will be confirmed to preside the production of Al-Ain oasis. In addition, plan of Al-Ain 2030 recommends protecting the vital water resources such as, but are not limited to, rainwater, groundwater, stormwater run-off, recycled industrial process water, desalinated water, recycled blackwater and recycled greywater. Moreover, some rules and several methods will be recognized for using water in different applications such as taps, toilets, appliances and showers. Especially for landscape and agricultural irrigation, the water recycling and re-use will be confirmed (Abu Dhabi Urban Planning Council (UPC), 2014).

4.3.5 Market Projections

According to the Urban Structure Framework Plan (Abu Dhabi Urban Planning Council (UPC), 2014) that based on the population and economic forecasts, the growth assumptions for the Al Ain city was achieved. The document shows the forecasting of urban area till year 2030. Moreover, the study used an accurate data of year 2005 to find an addition data for 2007. Then, the data in year 2007 has been prepared as a baseline to predict the land use requirement over the next twenty-two year. The Urban Structure Framework Plan showed that the population of Al Ain city in year 2005 was 284,040 and the five adjoining rural districts (Al Salamat, Al Yahar, Um Ghaffa, Al Dhaher and Mezyad) had a total population equal to 338,970. The population growth in baseline year 2007 was 374,000 and the annual tourist visits was 200,000 in the same year.

The Urban Structure Framework Plan was discussed the prediction of population growth, annual tourist visits, residential units and industry space of years 2020 and 2030. For year 2020, the data described as following; 627000 of residents, 710000 of annual tourist visits, 124290 of residential units, and 1450000 square meter of industry space. In addition, for year 2030, the data obtained as following; one million population growth, 1071000 of annual tourist visits, 202061 of residential units, and 1975000 square meter of industry space.

4.4 Database for Al Ain City

Various data are received from Al-Ain Distribution Company (AADC) and Abu-Dhabi Statistic Centre (SCAD). These collected data are classified according to different variables to predict water demand till year 2030 in Al-Ain city. In this study, the data of water consumption was collected from AADC and the data of independent variables which are population size and average temperature were collected from SCAD and AADC, respectively as follows:

4.4.1 Water Quantities

The monthly water consumption for seven different sectors (agricultural, residential, non-metered services, commercial, government, industrial, and public services) of Al-Ain city over the 15 years from 1998 to 2012 was received from AADC. Table 2 shows the annual water consumption (million cubic meters) of Al-Ain city.

Table 2: Monthly water consumption (in MCM) for each sector of the year 1998

1998								
Month/ Sector	Agricultural	Residential	Non-Metered Services	Commercial	Government	Industrial	Public Services	Total
January	0.543	1.953	0.051	0.152	0.608	0.015	0.038	3.359
February	0.276	1.787	0.051	0.144	0.784	0.002	0.032	3.077
March	0.307	2.685	0.062	0.213	0.183	0.013	0.045	3.508
April	0.304	2.639	0.065	0.259	0.771	0.010	0.062	4.111
May	0.543	2.833	0.104	0.252	1.101	0.020	0.048	4.901
June	0.417	2.382	0.064	0.214	0.803	0.021	0.043	3.944
July	0.337	2.771	0.076	0.224	0.833	0.016	0.049	4.305
August	0.339	2.024	0.096	0.255	1.499	0.015	0.051	4.279
September	0.305	2.573	0.065	0.160	0.785	0.011	0.048	3.947
October	0.676	1.871	0.051	0.219	0.883	0.010	0.050	3.759
November	0.321	2.559	0.072	0.209	0.406	0.010	0.048	3.626
December	0.342	2.133	0.061	0.187	0.695	0.011	0.042	3.471
Total	4.710	28.211	0.818	2.487	9.352	0.154	0.555	46.287

Table 3: Monthly water consumption (in MCM) for each sector of the year 1999

1999								
Month/ Sector	Agricultural	Residential	Non-Metered Services	Commercial	Government	Industrial	Public Services	Total
January	0.526	1.893	0.049	0.147	0.589	0.015	0.037	3.257
February	0.260	1.684	0.048	0.136	0.739	0.002	0.030	2.900
March	0.284	2.490	0.057	0.197	0.170	0.012	0.042	3.253
April	0.259	2.252	0.056	0.221	0.658	0.009	0.053	3.507
May	0.482	2.511	0.092	0.224	0.976	0.017	0.042	4.343
June	0.520	2.973	0.080	0.267	1.002	0.026	0.054	4.921
July	0.405	3.330	0.091	0.269	1.000	0.019	0.058	5.173
August	0.424	2.526	0.120	0.318	1.872	0.019	0.063	5.342
September	0.386	3.254	0.082	0.203	0.992	0.015	0.060	4.992
October	0.852	2.358	0.064	0.276	1.113	0.012	0.062	4.738
November	0.408	3.252	0.092	0.265	0.516	0.013	0.061	4.607
December	0.451	2.815	0.081	0.246	0.917	0.015	0.055	4.581
Total	5.257	31.338	0.913	2.769	10.545	0.173	0.619	51.615

Table 4: Monthly water consumption (in MCM) for each sector of the year 2000

2000								
Month/ Sector	Agricultural	Residential	Non-Metered Services	Commercial	Government	Industrial	Public Services	Total
January	0.744	2.678	0.070	0.208	0.834	0.021	0.053	4.607
February	0.364	2.354	0.067	0.190	1.033	0.003	0.042	4.053
March	0.377	3.300	0.076	0.261	0.225	0.016	0.055	4.311
April	0.324	2.820	0.070	0.277	0.824	0.011	0.067	4.392
May	0.505	2.634	0.096	0.235	1.024	0.018	0.044	4.557
June	0.493	2.817	0.076	0.253	0.950	0.025	0.051	4.664
July	0.388	3.190	0.087	0.258	0.958	0.018	0.056	4.956
August	0.422	2.518	0.120	0.317	1.866	0.019	0.063	5.324
September	0.414	3.496	0.088	0.218	1.066	0.016	0.065	5.363
October	1.113	3.079	0.084	0.360	1.454	0.016	0.082	6.187
November	0.480	3.829	0.108	0.312	0.607	0.015	0.072	5.423
December	0.499	3.111	0.089	0.272	1.014	0.017	0.061	5.063
Total	6.124	35.826	1.032	3.160	11.854	0.193	0.711	58.900

Table 5: Monthly water consumption (in MCM) for each sector of the year 2001

2001								
Month/ Sector	Agricultural	Residential	Non-Metered Services	Commercial	Government	Industrial	Public Services	Total
January	0.768	2.761	0.072	0.214	0.860	0.021	0.054	4.751
February	0.376	2.435	0.070	0.197	1.068	0.003	0.043	4.192
March	0.409	3.577	0.082	0.283	0.244	0.018	0.060	4.673
April	0.388	3.373	0.084	0.331	0.986	0.013	0.080	5.254
May	0.615	3.204	0.117	0.285	1.245	0.022	0.054	5.542
June	0.726	4.149	0.112	0.372	1.399	0.037	0.075	6.869
July	0.588	4.825	0.132	0.390	1.450	0.027	0.084	7.496
August	0.604	3.603	0.171	0.453	2.670	0.027	0.091	7.619
September	0.546	4.606	0.116	0.287	1.404	0.021	0.086	7.065
October	1.242	3.435	0.094	0.402	1.622	0.018	0.091	6.903
November	0.632	5.042	0.143	0.411	0.799	0.020	0.095	7.142
December	0.715	4.458	0.128	0.390	1.453	0.024	0.088	7.255
Total	7.607	45.468	1.320	4.016	15.200	0.249	0.900	74.760

Table 6: Monthly water consumption (in MCM) for each sector of the year 2002

2002								
Month/ Sector	Agricultural	Residential	Non-Metered Services	Commercial	Government	Industrial	Public Services	Total
January	1.135	4.084	0.106	0.317	1.272	0.032	0.080	7.027
February	0.573	3.704	0.106	0.299	1.626	0.005	0.065	6.378
March	0.689	6.034	0.139	0.478	0.412	0.030	0.101	7.884
April	0.584	5.075	0.126	0.498	1.483	0.019	0.120	7.905
May	0.908	4.734	0.173	0.422	1.840	0.033	0.080	8.190
June	0.937	5.359	0.144	0.481	1.806	0.047	0.097	8.872
July	0.770	6.320	0.173	0.511	1.899	0.036	0.111	9.818
August	0.763	4.552	0.216	0.573	3.373	0.034	0.114	9.625
September	0.724	6.107	0.154	0.380	1.862	0.027	0.114	9.367
October	1.764	4.882	0.133	0.571	2.305	0.025	0.129	9.809
November	0.819	6.532	0.185	0.533	1.035	0.025	0.123	9.253
December	0.954	5.953	0.171	0.521	1.939	0.032	0.117	9.686
Total	10.620	63.335	1.826	5.583	20.852	0.344	1.252	103.813

Table 7: Monthly water consumption (in MCM) for each sector of the year 2003

2003								
Month/ Sector	Agricultural	Residential	Non-Metered Services	Commercial	Government	Industrial	Public Services	Total
January	1.410	5.074	0.132	0.394	1.580	0.039	0.100	8.729
February	0.736	4.764	0.137	0.385	2.091	0.006	0.084	8.202
March	0.845	7.400	0.171	0.586	0.506	0.036	0.124	9.668
April	0.691	6.007	0.149	0.589	1.756	0.023	0.142	9.357
May	1.130	5.889	0.215	0.524	2.289	0.041	0.099	10.188
June	1.108	6.334	0.170	0.569	2.135	0.056	0.114	10.486
July	0.824	6.768	0.185	0.547	2.033	0.039	0.119	10.514
August	0.850	5.070	0.241	0.638	3.757	0.038	0.127	10.722
September	0.810	6.835	0.172	0.426	2.084	0.030	0.127	10.484
October	1.897	5.250	0.143	0.614	2.479	0.027	0.139	10.549
November	0.886	7.065	0.200	0.577	1.120	0.027	0.133	10.008
December	1.042	6.503	0.186	0.569	2.119	0.035	0.128	10.582
Total	12.231	72.960	2.102	6.417	23.948	0.397	1.437	119.490

Table 8: Monthly water consumption (in MCM) for each sector of the year 2004

2004								
Month/ Sector	Agricultural	Residential	Non-Metered Services	Commercial	Government	Industrial	Public Services	Total
January	1.655	5.955	0.155	0.462	1.854	0.046	0.117	10.245
February	0.870	5.631	0.161	0.455	2.471	0.007	0.099	9.695
March	0.954	8.349	0.192	0.661	0.570	0.041	0.140	10.907
April	0.789	6.854	0.170	0.672	2.003	0.026	0.162	10.675
May	1.242	6.477	0.237	0.577	2.518	0.045	0.109	11.205
June	1.434	8.198	0.220	0.736	2.763	0.072	0.148	13.572
July	1.170	9.606	0.262	0.776	2.886	0.055	0.168	14.923
August	1.194	7.123	0.339	0.896	5.278	0.053	0.179	15.063
September	1.123	9.477	0.239	0.590	2.890	0.042	0.176	14.538
October	2.665	7.374	0.201	0.862	3.481	0.038	0.195	14.817
November	1.234	9.847	0.279	0.804	1.561	0.038	0.186	13.948
December	1.354	8.448	0.242	0.739	2.752	0.045	0.166	13.747
Total	15.685	93.340	2.698	8.231	31.028	0.508	1.846	153.337

Table 9: Monthly water consumption (in MCM) for each sector of the year 2005

2005								
Month/ Sector	Agricultural	Residential	Non-Metered Services	Commercial	Government	Industrial	Public Services	Total
January	2.145	7.719	0.201	0.599	2.403	0.060	0.152	13.279
February	1.116	7.222	0.207	0.584	3.169	0.009	0.127	12.435
March	1.331	11.650	0.268	0.922	0.796	0.057	0.196	15.220
April	1.181	10.260	0.254	1.007	2.999	0.039	0.242	15.982
May	1.971	10.275	0.376	0.915	3.994	0.071	0.173	17.775
June	1.905	10.890	0.293	0.977	3.671	0.096	0.197	18.029
July	1.525	12.524	0.342	1.012	3.762	0.071	0.219	19.455
August	1.554	9.269	0.441	1.166	6.868	0.069	0.233	19.600
September	1.446	12.202	0.308	0.760	3.720	0.054	0.227	18.717
October	3.493	9.666	0.264	1.130	4.564	0.049	0.256	19.423
November	1.606	12.815	0.363	1.046	2.031	0.050	0.242	18.153
December	1.779	11.102	0.318	0.972	3.617	0.059	0.218	18.066
Total	21.053	125.593	3.634	11.090	41.595	0.685	2.482	206.133

Table 10: Monthly water consumption (in MCM) for each sector of the year 2006

2006								
Month/ Sector	Agricultural	Residential	Non-Metered Services	Commercial	Government	Industrial	Public Services	Total
January	2.804	10.089	0.263	0.783	3.141	0.078	0.199	17.357
February	1.462	9.458	0.271	0.764	4.151	0.012	0.167	16.284
March	1.686	14.759	0.340	1.168	1.008	0.073	0.248	19.283
April	1.456	12.652	0.313	1.241	3.698	0.048	0.299	19.707
May	2.393	12.474	0.456	1.111	4.850	0.087	0.210	21.581
June	2.262	12.932	0.347	1.161	4.359	0.114	0.233	21.408
July	1.790	14.699	0.402	1.187	4.416	0.084	0.257	22.834
August	1.781	10.623	0.505	1.337	7.871	0.079	0.267	22.463
September	1.625	13.708	0.346	0.853	4.179	0.061	0.255	21.026
October	3.794	10.499	0.287	1.228	4.957	0.054	0.278	21.096
November	1.791	14.288	0.405	1.166	2.265	0.055	0.270	20.240
December	1.751	10.924	0.313	0.956	3.559	0.058	0.214	17.775
Total	24.595	147.104	4.248	12.956	48.453	0.802	2.897	241.055

Table 11: Monthly water consumption (in MCM) for each sector of the year 2007

2007								
Month/ Sector	Agricultural	Residential	Non-Metered Services	Commercial	Government	Industrial	Public Services	Total
January	2.973	10.698	0.279	0.831	3.331	0.083	0.211	18.405
February	1.551	10.033	0.287	0.811	4.403	0.012	0.177	17.274
March	1.711	14.978	0.345	1.186	1.023	0.074	0.252	19.568
April	1.525	13.252	0.328	1.300	3.873	0.050	0.313	20.641
May	2.451	12.778	0.467	1.138	4.968	0.089	0.215	22.106
June	2.326	13.299	0.357	1.194	4.483	0.117	0.240	22.017
July	1.797	14.758	0.403	1.192	4.433	0.084	0.258	22.926
August	1.802	10.747	0.511	1.352	7.963	0.080	0.270	22.726
September	1.714	14.464	0.365	0.901	4.410	0.064	0.269	22.186
October	4.086	11.305	0.309	1.322	5.337	0.058	0.299	22.715
November	1.911	15.242	0.432	1.244	2.416	0.059	0.288	21.591
December	2.077	12.962	0.372	1.134	4.223	0.069	0.255	21.092
Total	25.924	154.514	4.455	13.604	50.863	0.840	3.047	253.245

Table 12: Monthly water consumption (in MCM) for each sector of the year 2008

2008								
Month/ Sector	Agricultural	Residential	Non-Metered Services	Commercial	Government	Industrial	Public Services	Total
January	3.154	11.349	0.296	0.881	3.534	0.088	0.223	19.525
February	1.715	11.093	0.318	0.896	4.868	0.014	0.196	19.099
March	1.752	15.341	0.354	1.214	1.048	0.075	0.258	20.043
April	1.538	13.366	0.331	1.311	3.907	0.051	0.315	20.819
May	2.470	12.877	0.471	1.147	5.006	0.089	0.217	22.277
June	2.322	13.276	0.357	1.192	4.475	0.117	0.240	21.978
July	1.784	14.648	0.400	1.183	4.400	0.083	0.256	22.755
August	1.803	10.751	0.511	1.353	7.966	0.080	0.270	22.733
September	1.713	14.454	0.365	0.900	4.407	0.064	0.269	22.172
October	3.997	11.059	0.302	1.293	5.221	0.056	0.293	22.220
November	1.782	14.217	0.403	1.160	2.254	0.055	0.269	20.139
December	1.960	12.231	0.351	1.070	3.985	0.065	0.240	19.903
Total	25.990	154.661	4.457	13.601	51.070	0.839	3.046	253.664

Table 13: Monthly water consumption (in MCM) for each sector of the year 2009

2009								
Month/ Sector	Agricultural	Residential	Non-Metered Services	Commercial	Government	Industrial	Public Services	Total
January	3.170	11.406	0.297	0.886	3.551	0.088	0.224	19.623
February	1.639	10.601	0.304	0.857	4.652	0.013	0.187	18.253
March	1.763	15.434	0.356	1.222	1.054	0.076	0.259	20.164
April	1.550	13.471	0.334	1.321	3.937	0.051	0.318	20.982
May	2.480	12.928	0.473	1.151	5.026	0.090	0.218	22.366
June	2.284	13.055	0.351	1.172	4.400	0.115	0.236	21.612
July	1.776	14.587	0.398	1.178	4.382	0.083	0.255	22.660
August	1.834	10.935	0.520	1.376	8.103	0.081	0.275	23.123
September	1.673	14.119	0.356	0.879	4.305	0.063	0.262	21.658
October	4.055	11.220	0.306	1.312	5.297	0.057	0.297	22.545
November	1.898	15.142	0.429	1.236	2.400	0.059	0.286	21.449
December	2.021	12.608	0.361	1.103	4.107	0.067	0.248	20.516
Total	26.142	155.506	4.485	13.693	51.216	0.844	3.066	254.951

Table 14: Monthly water consumption (in MCM) for each sector of the year 2010

2010								
Month/ Sector	Agricultural	Residential	Non-Metered Services	Commercial	Government	Industrial	Public Services	Total
January	3.272	11.771	0.307	0.914	3.665	0.091	0.232	20.250
February	1.706	11.036	0.316	0.892	4.843	0.013	0.195	19.001
March	1.894	16.581	0.382	1.313	1.133	0.082	0.279	21.663
April	1.499	13.024	0.323	1.278	3.807	0.049	0.307	20.287
May	2.614	13.629	0.498	1.214	5.299	0.095	0.230	23.579
June	2.359	13.486	0.362	1.210	4.545	0.119	0.243	22.325
July	1.671	13.720	0.375	1.108	4.122	0.078	0.240	21.314
August	1.626	9.694	0.461	1.220	7.183	0.072	0.244	20.499
September	1.579	13.322	0.336	0.829	4.062	0.059	0.248	20.435
October	3.833	10.607	0.290	1.240	5.008	0.054	0.281	21.314
November	1.748	13.941	0.395	1.138	2.210	0.054	0.263	19.749
December	2.024	12.628	0.362	1.105	4.114	0.068	0.248	20.549
Total	25.824	153.440	4.406	13.461	49.990	0.835	3.009	250.964

Table 15: Monthly water consumption (in MCM) for each sector of the year 2011

2011								
Month/ Sector	Agricultural	Residential	Non-Metered Services	Commercial	Government	Industrial	Public Services	Total
January	3.183	11.453	0.298	0.889	3.566	0.089	0.225	19.705
February	1.623	10.502	0.301	0.848	4.609	0.013	0.185	18.081
March	1.783	15.605	0.360	1.235	1.066	0.077	0.262	20.387
April	1.540	13.381	0.331	1.313	3.911	0.051	0.316	20.842
May	2.509	13.080	0.478	1.165	5.085	0.091	0.221	22.629
June	2.384	13.630	0.366	1.223	4.594	0.120	0.246	22.564
July	1.828	15.012	0.410	1.213	4.510	0.085	0.263	23.321
August	1.883	11.228	0.534	1.413	8.320	0.084	0.282	23.743
September	1.659	14.000	0.353	0.872	4.268	0.062	0.260	21.475
October	4.277	11.834	0.323	1.384	5.587	0.060	0.313	23.779
November	1.939	15.467	0.438	1.262	2.452	0.060	0.292	21.911
December	2.199	13.720	0.393	1.201	4.470	0.073	0.269	22.326
Total	26.807	158.913	4.586	14.018	52.438	0.865	3.135	260.762

Table 16: Monthly water consumption (in MCM) for each sector of the year 2012

2012								
Month/ Sector	Agricultural	Residential	Non-Metered Services	Commercial	Government	Industrial	Public Services	Total
January	3.619	13.022	0.339	1.011	4.055	0.101	0.256	22.404
February	1.882	12.173	0.349	0.983	5.342	0.015	0.215	20.958
March	2.048	17.928	0.413	1.419	1.225	0.088	0.301	23.423
April	1.683	14.631	0.362	1.435	4.276	0.055	0.345	22.789
May	2.799	14.590	0.533	1.299	5.672	0.101	0.246	25.241
June	2.549	14.572	0.392	1.308	4.912	0.129	0.263	24.124
July	2.009	16.501	0.451	1.333	4.957	0.094	0.289	25.633
August	2.018	12.037	0.572	1.515	8.919	0.090	0.303	25.455
September	1.957	16.515	0.417	1.028	5.035	0.074	0.307	25.333
October	4.506	12.468	0.340	1.458	5.886	0.064	0.330	25.053
November	2.161	17.239	0.488	1.407	2.733	0.067	0.326	24.420
December	2.274	14.189	0.407	1.242	4.623	0.076	0.279	23.089
Total	29.506	175.865	5.063	15.439	57.635	0.953	3.459	287.921

4.4.2 Population

The population data covering the period of 1997 to 2012 that was taken from Abu-Dhabi Statistic Centre (SCAD) is shown in the Table 3. The population size has a vital effect on the water demand forecasting.

4.4.3 Temperature

Values of the average monthly temperature in Al Ain City over the past 15 years (1998–2012) were received from AADC. Table 4 summarizes the average annual temperature yearly during the periods of 1998 - 2012.

4.4.4 Database Quality

There are some uncertainties in the data received from AADC. For example, the water consumption of the agricultural sector in July during years 1998-2009 was recorded as a negative value. This concern was discussed to AADC to explain the negative values, and below is the summary of their points on this issue:

1. Reading procedures: according to Central Supplier Database (CSD) which sends the data to AADC, the readings were taken every month for each type of connected and metered customer. However, if readings were not taken for a particular month, an average consumption reading is carried out.
2. Recording procedure: the CSD has appraised the AADC that recording of consumption was not carried out immediately i.e., if a reading was taken in the month of January, it might be recorded only in March, and February will have no reading that makes the reading for February to be ‘negative’. But, if the reading was conducted on March the corresponding consumption quantity will be almost

double (twice) the monthly average. This is because the reading intended for February has been added to March actual reading to be combined as “March” reading. There is a human intervention that causes this problem of ‘negative’ consumption.

Table 17: Mid-year population of Al Ain city from 1997 to 2012

Year/ Month	January	February	March	April	May	June	July	August	September	October	November	December
1998	337008	337867	338725	339583	340442	341300	342158	343017	343875	344733	345592	346450
1999	346958	347767	348575	349383	350192	351000	351808	352617	353425	354233	355042	355850
2000	356591	357389	358188	358987	359785	360584	361383	362181	362980	363779	364577	365376
2001	367042	367965	368887	369810	370732	371655	372578	373500	374423	375345	376268	377191
2002	377193	377984	378775	379566	380357	381148	381939	382730	383521	384312	385103	385895
2003	386958	387788	388618	389448	390278	391108	391938	392768	393598	394428	395258	396088
2004	406765	409001	411238	413475	415711	417948	420185	422421	424658	426895	429131	431368
2005	433553	435783	438012	440241	442471	444700	446929	449159	451388	453617	455847	458076
2006	458280	460220	462160	464100	466040	467980	469920	471860	473800	475740	477680	479620
2007	479635	481300	482965	484630	486295	487960	489625	491290	492955	494620	496285	497950
2008	504719	507113	509507	511901	514295	516689	519083	521477	523871	526265	528659	531054
2009	531562	533686	535811	537936	540060	542185	544310	546434	548559	550684	552808	554933
2010	557373	559542	561712	563882	566051	568221	570391	572560	574730	576900	579069	581239
2011	584335	586637	588939	591241	593543	595845	598147	600449	602751	605053	607355	609657
2012	616355	619285	622215	625145	628075	631005	633935	636865	639795	642725	645655	648585

Table 18: Average temperature of Al-Ain city from 1998 to 2012

Year/ Month	January	February	March	April	May	June	July	August	September	October	November	December
1998	19.15	21.05	24.75	28.00	32.10	35.30	36.90	37.75	34.45	30.65	25.75	22.60
1999	19.85	22.50	22.65	28.75	31.25	35.10	36.05	38.60	34.35	30.70	26.00	21.00
2000	19.85	22.30	23.85	29.65	32.95	35.05	35.85	37.00	34.15	30.85	25.75	21.60
2001	17.15	20.00	24.10	28.65	33.35	35.90	36.55	36.55	35.40	30.70	25.75	23.65
2002	19.00	21.05	25.15	29.30	33.50	35.15	35.75	37.45	34.85	31.50	24.65	21.00
2003	18.65	21.95	24.90	29.15	32.05	35.85	35.50	37.50	35.05	31.35	25.30	21.35
2004	20.50	21.70	25.80	30.45	33.15	34.55	36.65	36.85	34.85	30.90	25.70	20.40
2005	19.55	19.90	25.15	28.75	31.75	35.45	36.00	37.70	34.25	30.50	26.75	21.95
2006	18.05	22.75	24.20	28.30	34.25	36.50	36.65	37.20	33.00	32.30	26.35	20.50
2007	18.15	22.70	23.90	28.70	33.15	37.60	36.65	37.95	34.90	29.70	25.90	19.95
2008	17.05	19.95	24.70	29.05	32.50	36.05	37.15	36.55	34.35	30.90	26.10	19.20
2009	18.95	23.55	24.45	28.60	33.80	35.25	37.45	37.05	34.55	31.45	26.10	21.85
2010	19.95	22.45	26.75	29.25	33.05	36.85	37.65	36.50	34.60	31.00	23.70	21.05
2011	20.20	20.85	25.30	28.25	33.35	36.30	36.80	37.35	34.95	31.05	24.15	19.10
2012	17.75	20.65	23.85	29.80	34.20	35.10	37.95	37.15	36.10	30.80	24.90	21.70

Chapter 5: Model Calibration and Verification

IWR-MAIN model has been used for projecting long-term demands of different urban water use. Two forecasting models, which are constant use rate model and linear forecasting model are used to predict future water use in Al-Ain city for seven sectors. These sectors are residential, agricultural, commercial, government, industrial, public services, and non-metered services. Three steps are followed for both models. In the first step, the model is calibrated using data from year 1998 to year 2012. Selection of the best base year is conducted in the second step. In the third step, prediction of the water demand from year 2013 to year 2030 are simulated. The following sections provide more detailed description of the model calibration and predictions using the two different forecasting methods.

Several factors that affect the rate of water use could be considered in this study. However, the only available data are population of Al-Ain city from 1998 to 2012, the average monthly temperature, during the same period, and the average rainfall for twelve months. The data were analyzed statistically using analysis of variance (ANOVA). The Statistical Package for Social Science (SPSS), Version 21 for Windows was used to analyze the available data. Statistical significance is attained when a p-value is equal to or smaller than significance (α) level ($p \leq 5$ %). If the p-value is less than or equal to significance level, then the null hypothesis is rejected because it usually refers to a hypothesis of "no difference". Based on this analysis, the water consumption, the dependent variable in this study, is considered significant with the population size because p-value is equal to 0.000 which is less than 0.05. Whereas, the water consumption is not significant with the temperature and rainfall because the calculated p-value was 0.394 and 0.232, respectively, which is greater than 0.05. Thus, the population size of Al-Ain city will be used as the only independent variable in this study.

The IWR-MAIN program has four water use forecasting methods; constant use rate, build forecasting model, specify forecasting model/multiplicative, and specify forecasting model/linear (as shown in Chapter 3). Each of these methods requires a specific set of input data as described earlier in Chapter 3. Based on the collected data, only two models are used in this research; namely, the constant use rate model and the linear forecasting model. Calibration of both models is described in the following sections.

5.1 Calibration of Model 1: Constant Use Rate Model

This model requires the water demand as a base year and the population size as input data. The earliest year entered in the IWR-MAIN program is designated as the base year. Therefore, thirteen calibration trials were performed using this model to opt the base year with most accurate water demand forecasting results. Basically, the equation of the constant use rate model includes on the rate of water use (q) in each sector for base year only multiplied by the counting units (N) in each sector for all years including the base year (Eq. 4 in Chapter 3). In the following subsections, yearly and monthly data for water use are simulated for each water sector. Database 1 represents data of total annual water use and database 2 represents annual data of water use in each sector. Moreover, database 3 represents data of total monthly water use and database 4 represents monthly data of water use in each sector.

5.1.1 Database 1

The first step in the calibration process is to enter water use rate per unit in the base year and the number of counting units for all simulated years in IWR-MAIN program. The value of counting units in this study is the population size of Al-Ain city. The first trial was simulated from 1998 to 2012. The values of annual water demand for all sectors from years 1998 to 2012 were simulated by IWR-MAIN.

Several trials of calibration were simulated. Figure 8 illustrates the calibration results of the thirteen trials by the different base years.

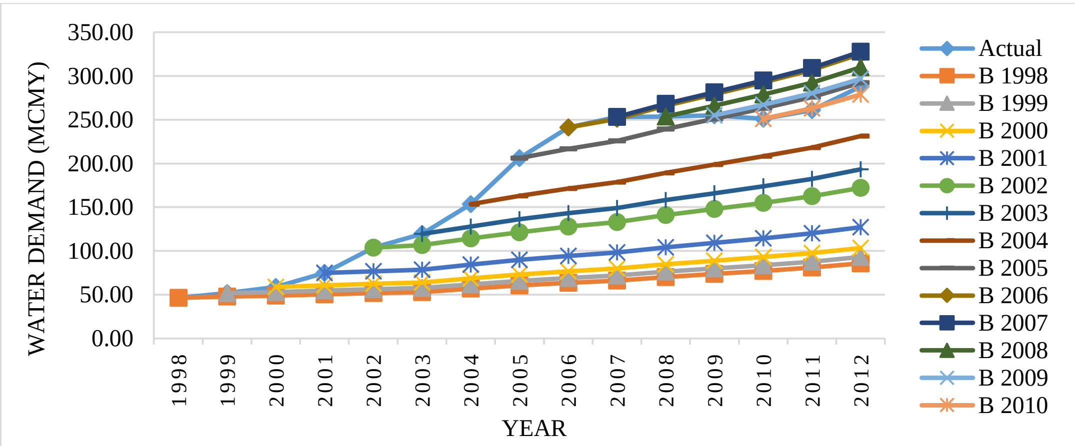


Figure 8: Actual and simulated total annual water use (database 1) using model 1

Figure 8 illustrates the actual and simulated total water use from 1998 to 2012 for the different calibration periods using database 1. The actual water consumption is generally increasing with time except in year 2010. However, the demand is slightly increased in the years 2008, 2009, and 2011. The highest actual water use is encountered in year 2012. The difference between the actual and simulated water use reflects errors in the amount of water use due to increased number of users. All calibration simulations are gradually increasing throughout the calibration period.

This is because using constant use rate model of IWR-MAIN, and this model depends on the changes in population so, the results do not show fluctuations in the simulated water use.

The second step in the calibration process is to compare between the actual water use and simulated water use for all selected base years. The calibration with minimum simulated error will be used in the forecasting scenarios. Equations (10 - 13) illustrate errors calculated for each calibration simulation including the absolute relative error (AREi), the average absolute relative error (AARE), the standard deviation of the absolute relative error (SDARE), and the average root mean square error (ARMSE).

$$\mathrm{ARE_i} = \frac{\mathrm{CD_i} - \mathrm{AD_i}}{\mathrm{AD_i}} \times 100 \quad \text{(Eq. 10)}$$

$$\mathrm{AARE} = \frac{1}{n} \sum_{i=1}^{n} \mathrm{ARE_i} \quad \text{(Eq. 11)}$$

$$\mathrm{SDARE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\mathrm{ARE_i} - \mathrm{AARE})^2} \quad \text{(Eq. 12)}$$

$$\mathrm{ARMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(\frac{\mathrm{CD_i} - \mathrm{AD_i}}{\mathrm{AD_i}}\right)^2} \quad \text{(Eq. 13)}$$

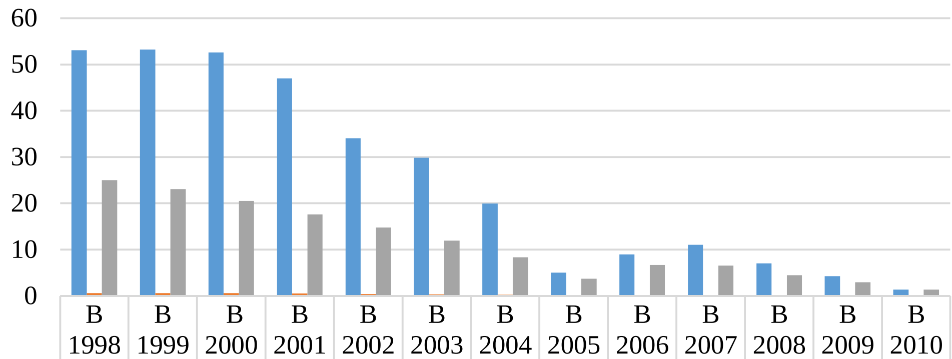
Where:

CD_i is the calibrated demand of year i of the calibration period

AD_i is the actual demand of year i of the calibration period

n is the number of years in the calibration period

According to these equations, the error values were calculated for each calibration simulation. Figure 9 summarizes the calculated values of AARE, ARMSE and SDARE for all calibration simulations with different base years.



	B 1998	B 1999	B 2000	B 2001	B 2002	B 2003	B 2004	B 2005	B 2006	B 2007	B 2008	B 2009	B 2010
AARE	53	53	53	47	34	30	20	5	9	11	7	4	1
ARMSE	0.6	0.6	0.6	0.5	0.4	0.3	0.2	0.1	0.1	0.1	0.1	0.1	0.0
SDARE	25	23	20	18	15	12	8	4	7	7	4	3	1

Figure 9: Error values of all calibration simulations for database 1 using model 1

Figure 9 shows that the values of calculated errors are generally decreasing when the calibration period is short. However, the simulation with base year 2005 shows minimum errors compared to simulation with base year 2006. Whereas, the calculated AARE for the simulation with base year 2007 is higher than the value obtained for the simulation with base year 2006. This might be because the actual water consumption during the years from 2006 to 2011 almost had the same magnitude and the difference between each other is less than 5%. The simulation with base year 2010 shows the least errors compared to other calibration simulations.

The calibration simulation with minimum AARE will be selected. If two simulations have the same AARE, then the simulation with longer calibration period and/or minimum SDARE will be selected. Based on this criteria, the calibration simulation with base year 2010 is selected in this model for database 1 to be used in forecasting water demand until year 2030.

5.1.2 Database 2

There are seven different sectors identified in Al-Ain city. Data available from these sectors are used in this study through the calibration process. Same calibration procedures will be followed for this database and all coming databases. The annual water use for each sector is used in this section. Thirteen simulations were conducted using different base years for each sector.

Figure 10 displays the actual and simulated annual water use for each sector for different base years from 1998 to 2012. Figure 10 also shows that the highest water use is in residential sector, whereas, the lowest water use is in industrial sector. The simulated demand becomes near to the actual demand when the calibration period becomes short.

Furthermore, using equations (Eqs. 10, 11, 12 and 13), the average absolute relative error (AARE) was calculated for all base years of the calibration simulations for each sector. The root mean square error (RMSE) and the standard deviation of the absolute relative error (SDARE) were also calculated for all base years of the calibration periods for each sector.

Figure 11 summarizes the calculated errors for all calibrated base years for each sector.

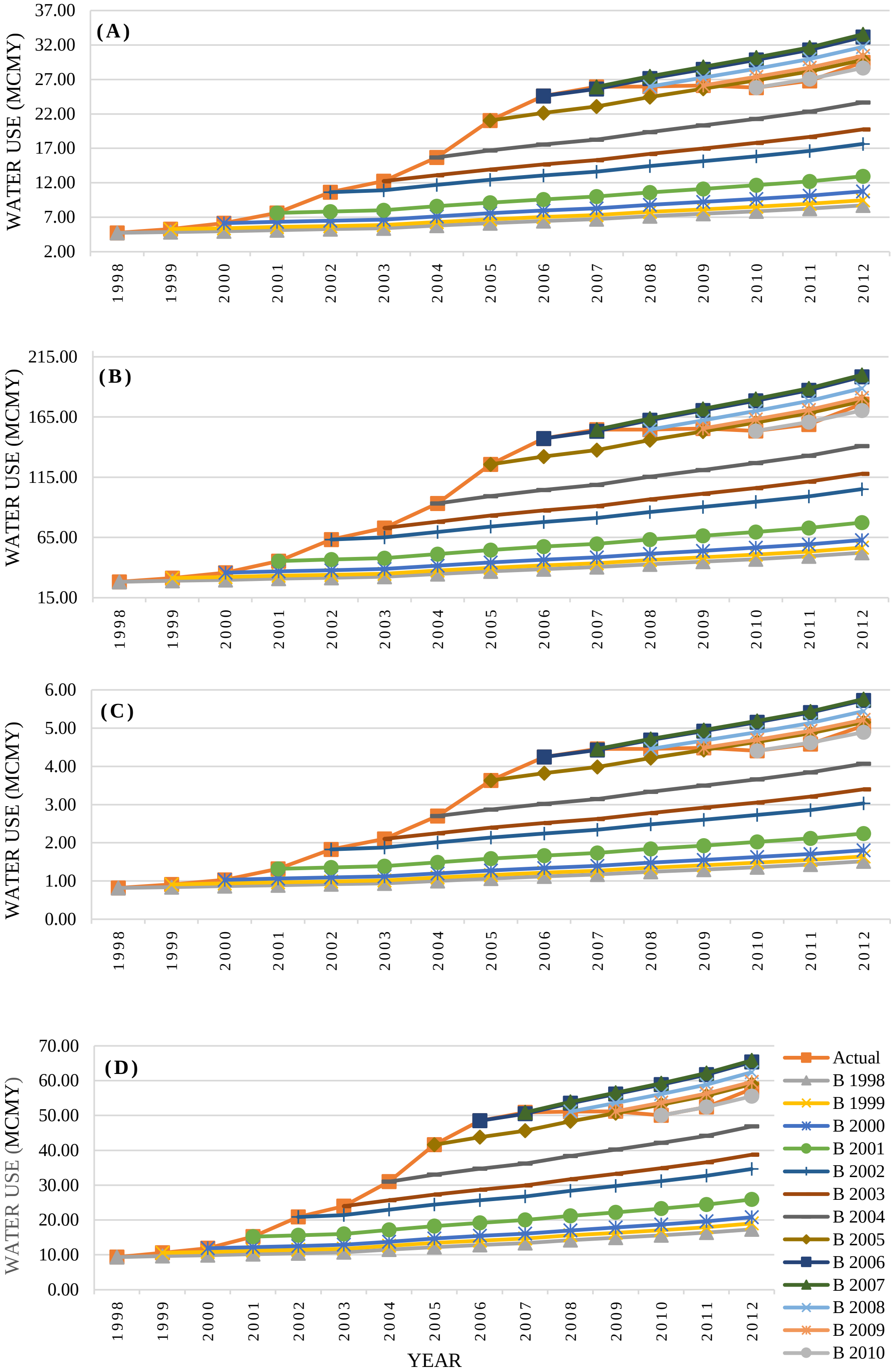


Figure 10: Actual and simulated total annual water use (database 2) using model 1 for (A) agricultural, (B) residential, (C) non-metered services, and (D) government

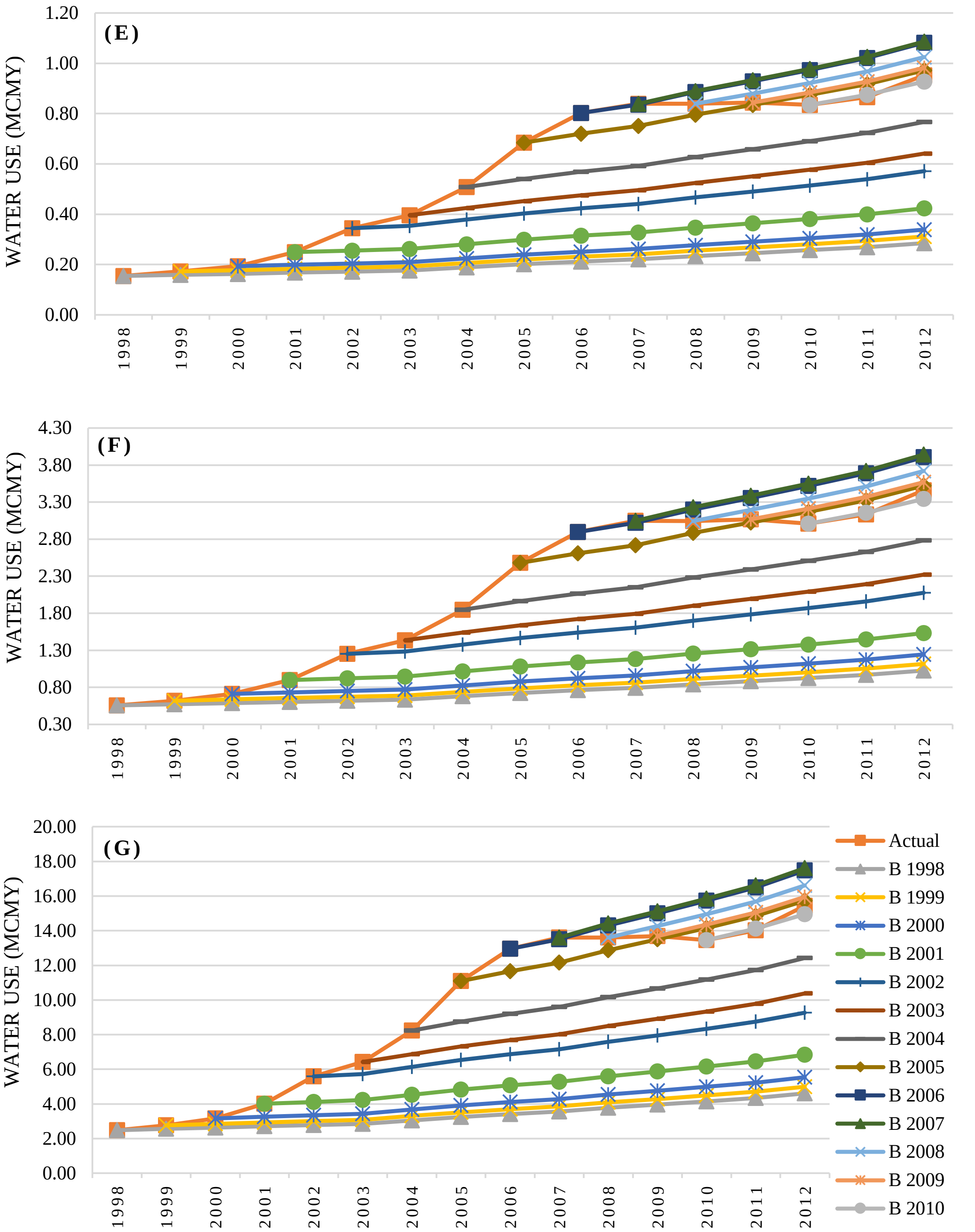


Figure 10: Actual and simulated total annual water use (database 2) using model 1 (E) industrial, (F) public services, and (G) commercial (Continued)

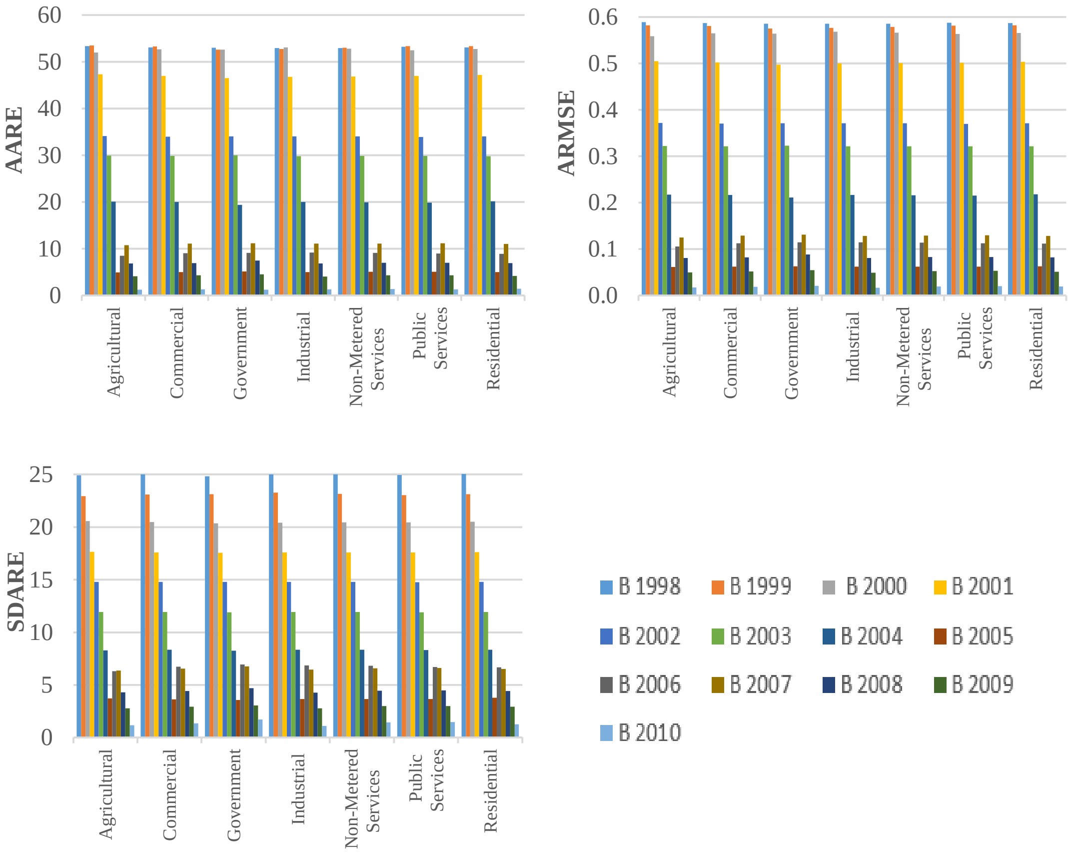


Figure 11: Error values of all calibration simulations for database 2 using model 1

Figure 11 shows that the AARE for simulation of base year 1999 is higher than AARE for simulation of base year 1998 in all sectors except for government and industrial sectors. However, ARMSE and SDARE demonstrate that the simulation of base year 1998 has the largest error compared to other base years for all sectors. Generally, AARE and ARMSE show that the simulation of base year 2007 has higher error than simulation of base year 2006. The values of SDARE for all sectors show that the simulation of base year 2007 has lesser error than in simulation of base year 2006, except for the agricultural sector. Figure 11 also shows that the last calibration simulation (base year 2010) represents the least error compared to other calibration simulations in all sectors. This comparison between the calibration simulations was performed in order to choose the most suitable base year with less error to build up the future forecasting scenarios.

Following the same criteria, used in database 1, of choosing the best base year, 2010 is considered as the most suitable base year for this database to predict the water demand from 2013 to 2030.

5.1.3 Database 3

Database 3 represents monthly data of total water use in all sectors. Same procedures were used to calibrate all sectors of database 3. Figure 12 presents the calibrated water use in million cubic meters per month for all sectors of the thirteen different base years as simulated using IWR-MAIN program.

Figure 12 shows that the actual water consumption is generally increasing with time except for specific months in 2010 and 2011. The highest actual consumption is encountered in 2012 and the highest monthly consumption is observed in July in the same year. July is the hottest month (average temperature is 38^{o}C) of the year so, large amount of water is consumed during this month (AADC, 2015). In the same year, the lowest monthly consumption is observed in February. This explains that February is a rainy month in Al-Ain city so, the average irrigation water consumption depends on the amount of rainfall (average precipitation is 4.3 mm) that may decrease the total water consumption in that month (SCAD, 2015). In addition, the absolute temperature in February is low (average of 21^{o}C in year 2012), that may decrease the total water consumption in that month (AADC, 2015).

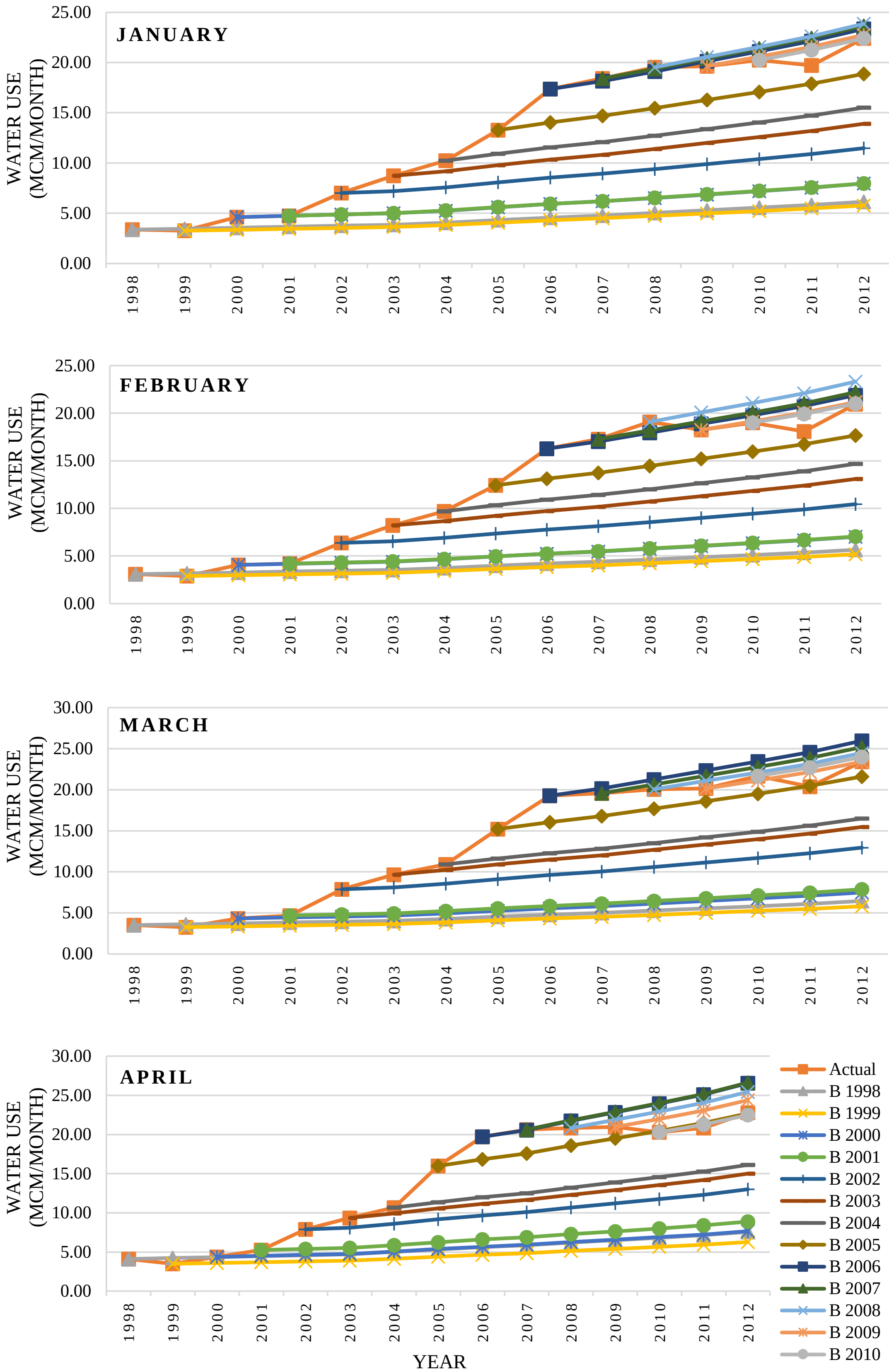


Figure 12: Actual and simulated total monthly water use (database 3) using model 1

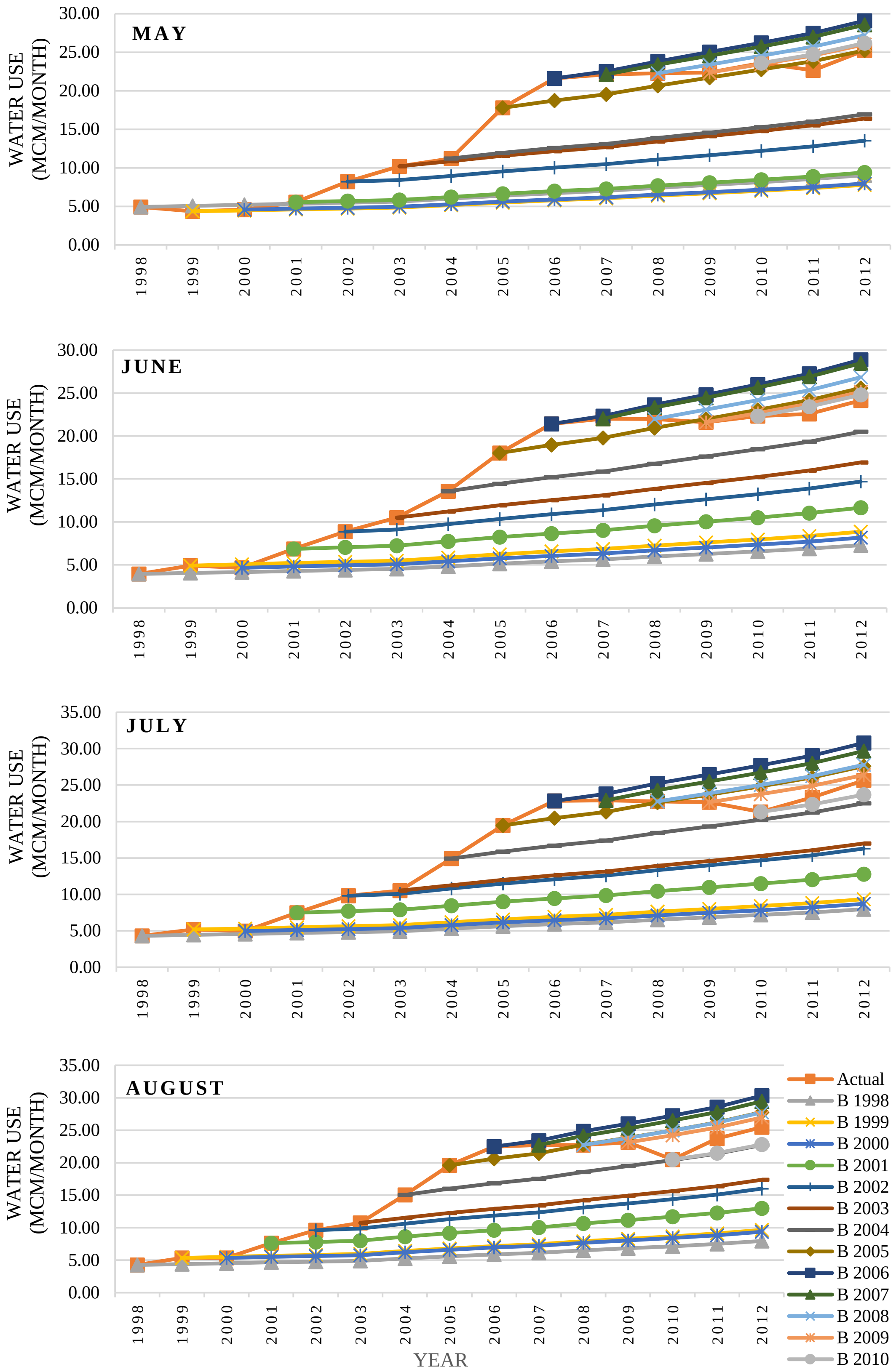


Figure 12: Actual and simulated total monthly water use (database 3) using model 1

(Continued)

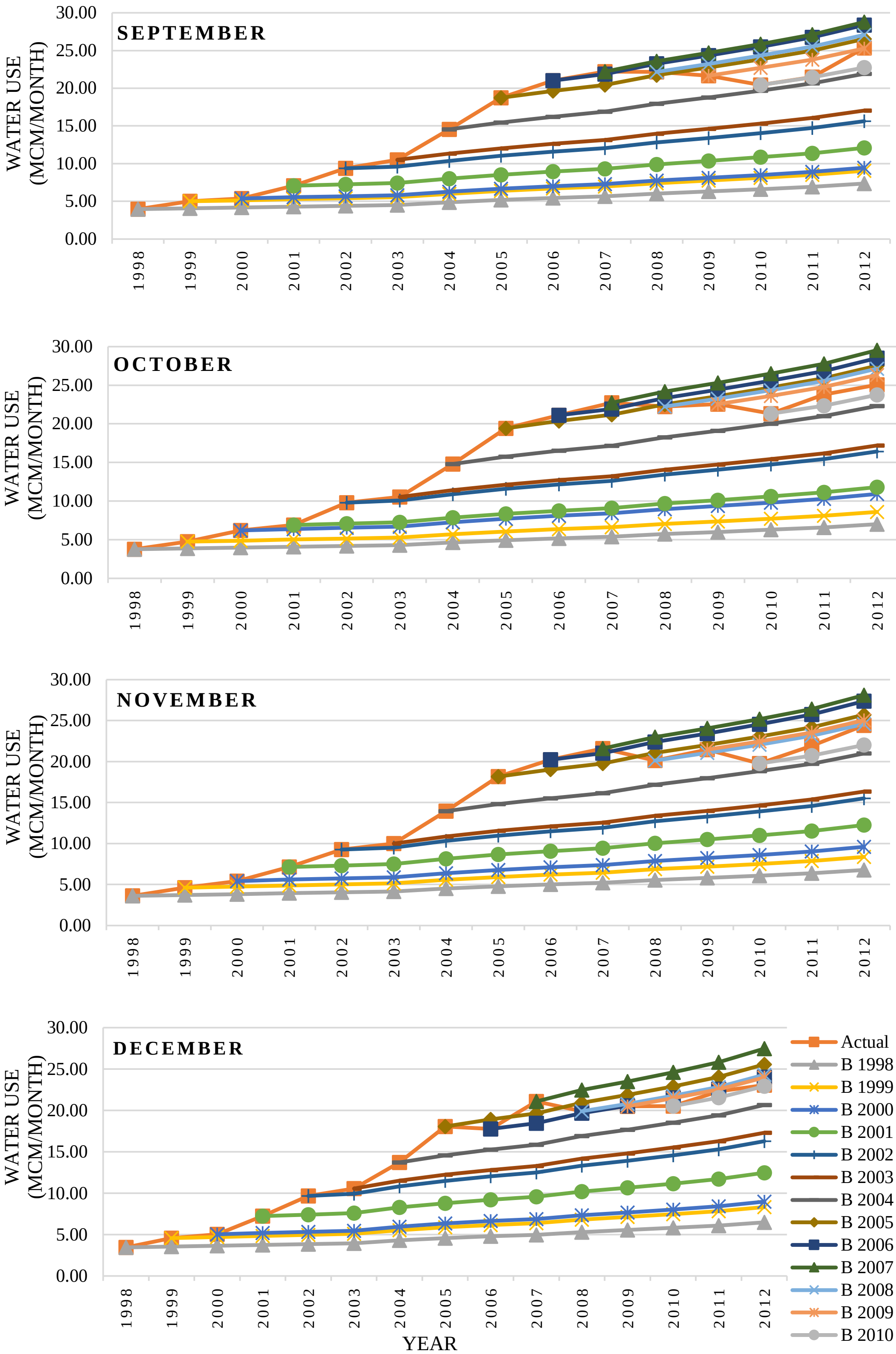


Figure 12: Actual and simulated total monthly water use (database 3) using model 1

(Continued)

The values of AARE, RMSE, and SDARE were calculated monthly water use of the calibration periods based on the equations (10, 11, 12, and 13). So, the values of error were analyzed and summarize in Figure 13.

Figure 13 shows that the simulation of base year 1999 holds the highest AARE and ARMSE for the month of March. The simulation of base year 1998 presents the highest SDARE for all months of the year, except the month of May that shows the highest SDARE for simulated base year 1999. Figure 13 also demonstrates that the last calibration simulation (base year 2010) displays the least AARE, ARMSE, and SDARE. Table 19 shows the best base year for each month that will be considered for the forecasting scenarios.

Table 19: Best base year for database 3 using model 1

Month	Base Year	Month	Base Year
January	2009	July	2010
February	2009	August	2005
March	2009	September	2010
April	2010	October	2010
May	2009	November	2008
June	2009	December	2010

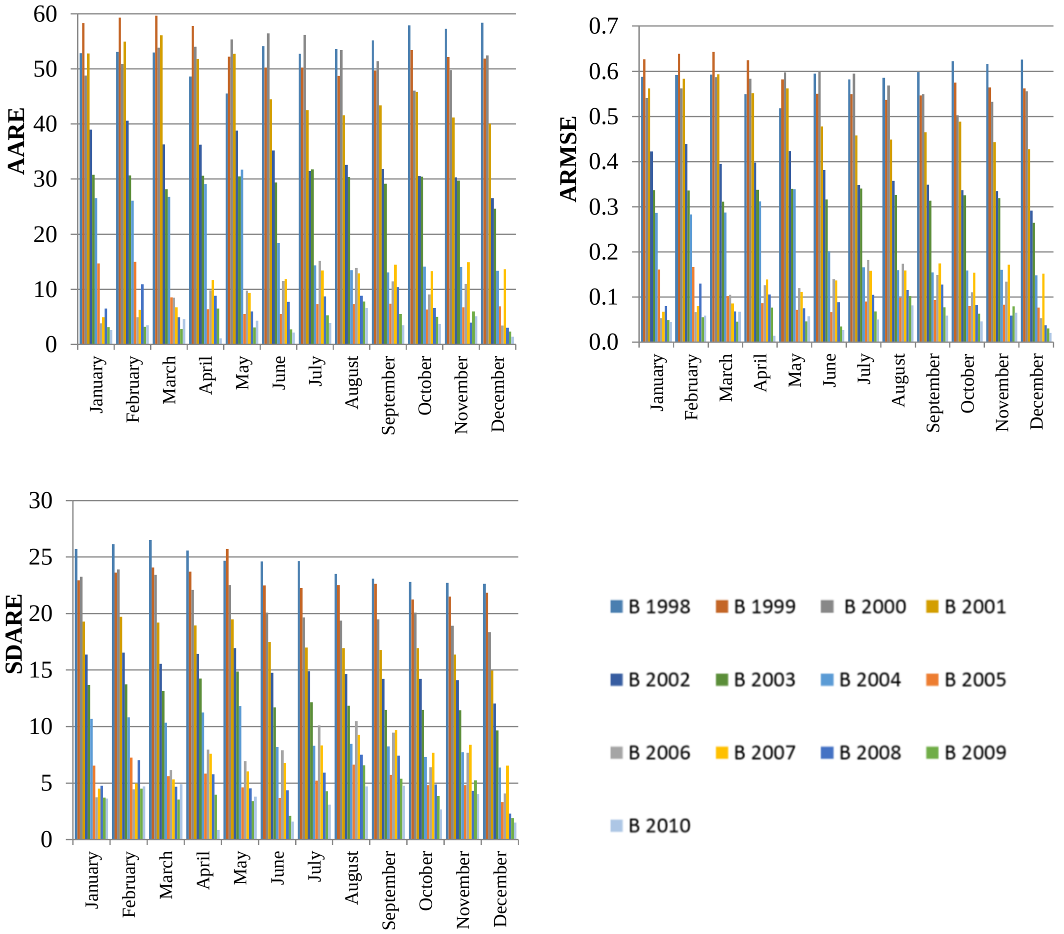


Figure 13: Error values of all calibration simulations for database 3 using model 1

5.1.4 Database 4

Seven different sectors were calibrated monthly by various base years. To simplify the results, each sector is discussed separately below.

5.1.4.1 Agricultural Sector

Figure 14 presents the actual and simulated monthly water use for agricultural sector with different base years.

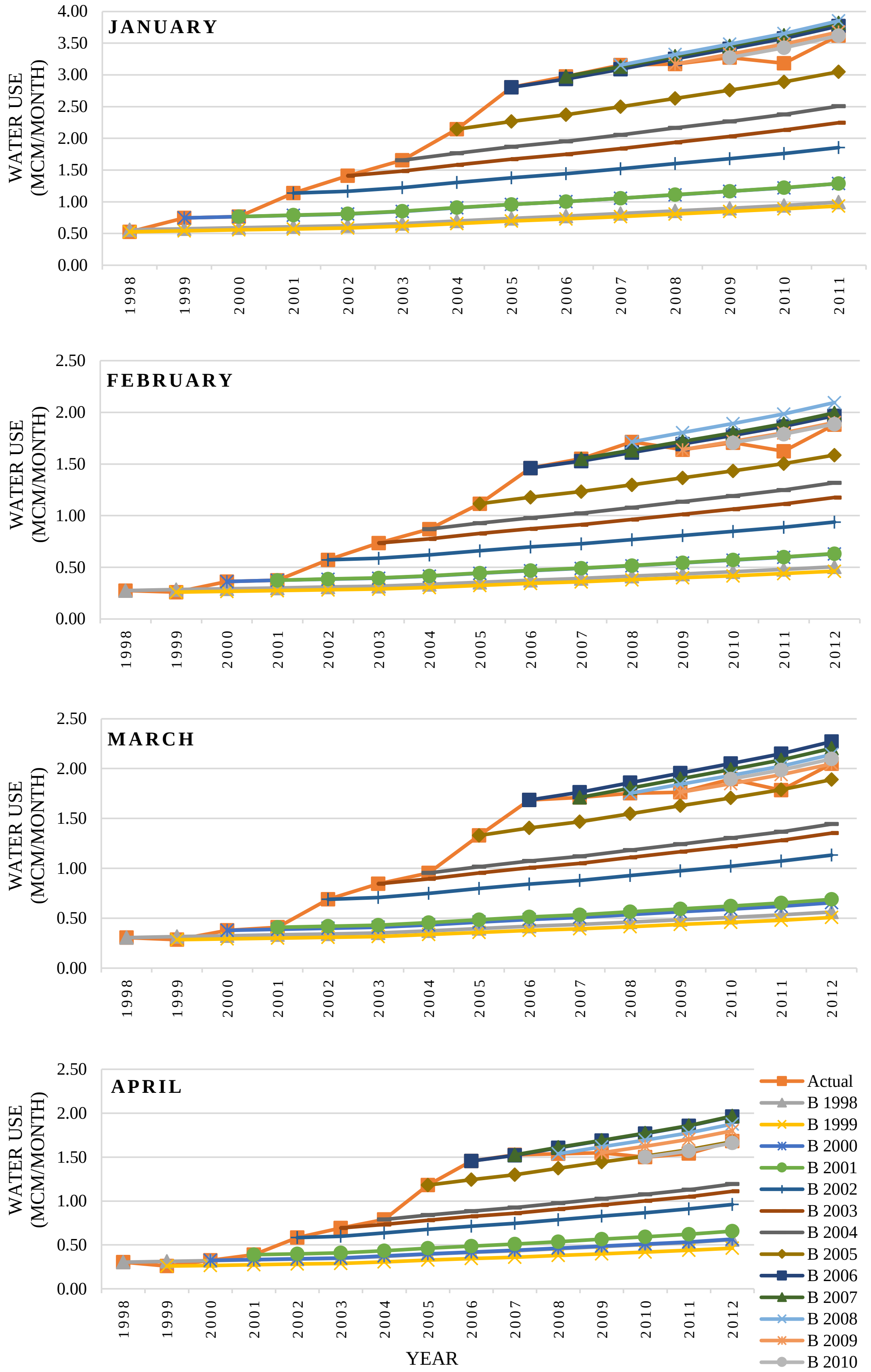


Figure 14: Actual and simulated monthly water use for agricultural sector using model 1

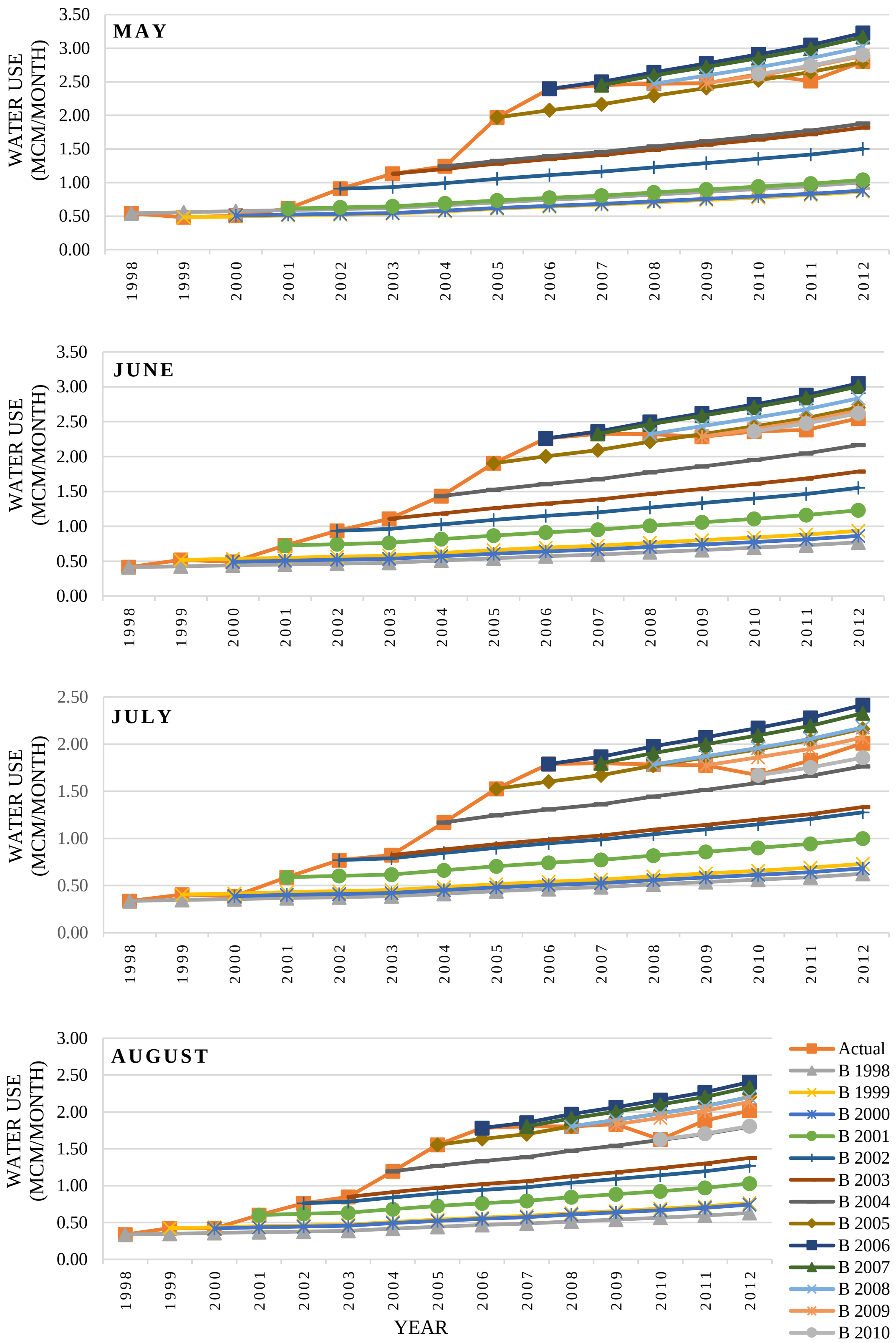


Figure 14: Actual and simulated monthly water use for agricultural sector using model 1

(Continued)

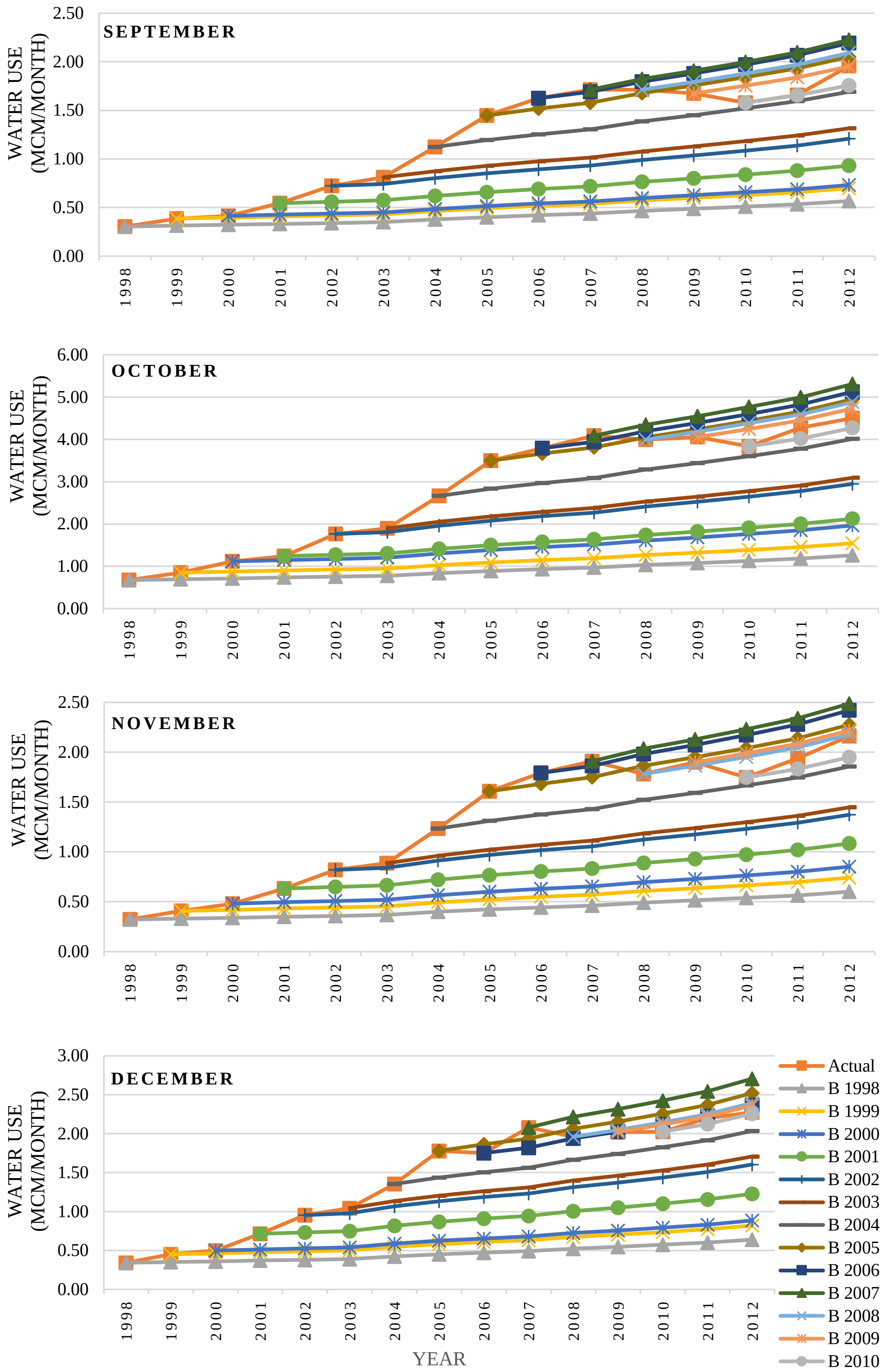


Figure 14: Actual and simulated monthly water use for agricultural sector using model 1

(Continued)

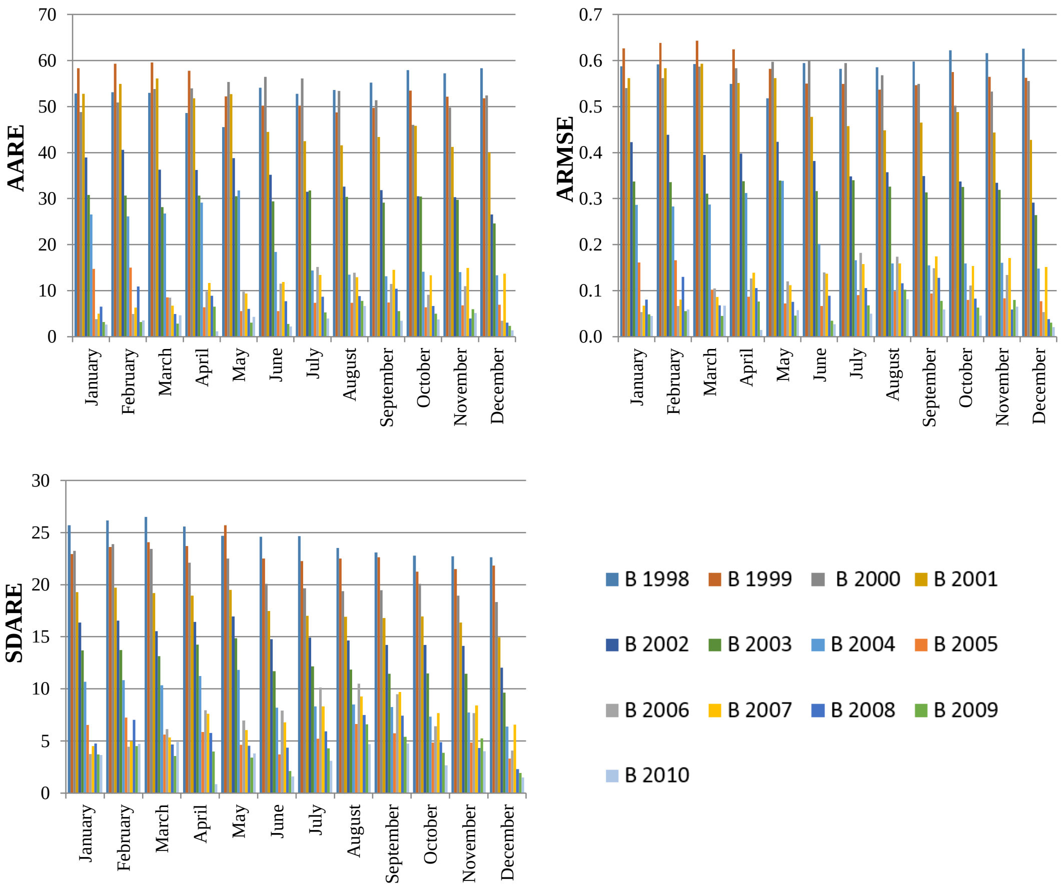


Figure 15: Error values of all calibration simulations for agricultural sector (database 4) using model 1

Figure 14 shows that the actual water use is generally increasing throughout the calibration period except for specific months in 2010 and 2011. The highest actual consumption is encountered in 2012. In this year, the highest monthly consumption is observed in October. Although, October is not the hottest month of the year (average temperature is 31°C), but most of the residents come back to work and school after spending summer holidays outside UAE (AADC, 2015). So, the amount of water use in home gardening in summer season is lesser than other months. This contributes to the apparent increase in water use of October, compared to the other hotter months of the summer such as June, July, August, and September.

Figure 15 demonstrates the AARE, ARMSE, and SDARE for the 12 months of the year for all simulated base years. It shows that the calibration simulation with base year 2010 has the least error occurred in April, July, September, October, and December. March displays the highest AARE and ARMSE for simulated base year 1999 and the highest SDARE for simulated base year 1998. Following the same criteria used in previous databases, year 2009 would be the best base year to forecast future demand in January, February, March, May, and June, while years 2005 and 2008 would be the best for August and November, respectively.

5.1.4.2 Residential Sector

Figure 16 illustrates the actual and simulated water use for residential sector with different base years. Figure 16 shows that the highest actual consumption is encountered in 2012. In this year, the highest monthly consumption is observed in March (average temperature is 24^{o}C and average precipitation is 0.5 mm) and the lowest monthly consumption is observed in February (average temperature is 21^{o}C) (AADC and SCAD, 2015).

Figure 17 represents the calculated AARE, ARMSE, and SDARE for all calibration simulations for the 12 months of the year. Figure 17 is used to select the best base year to forecast monthly water demand for residential sector. The results concluded that the base year 2010 is selected for April, July, September, October, and December. Also, year 2009 would be the best base year to forecast future demand in January, February, March, May, and June. While, years 2005 and 2008 would be the best for August and November, respectively.

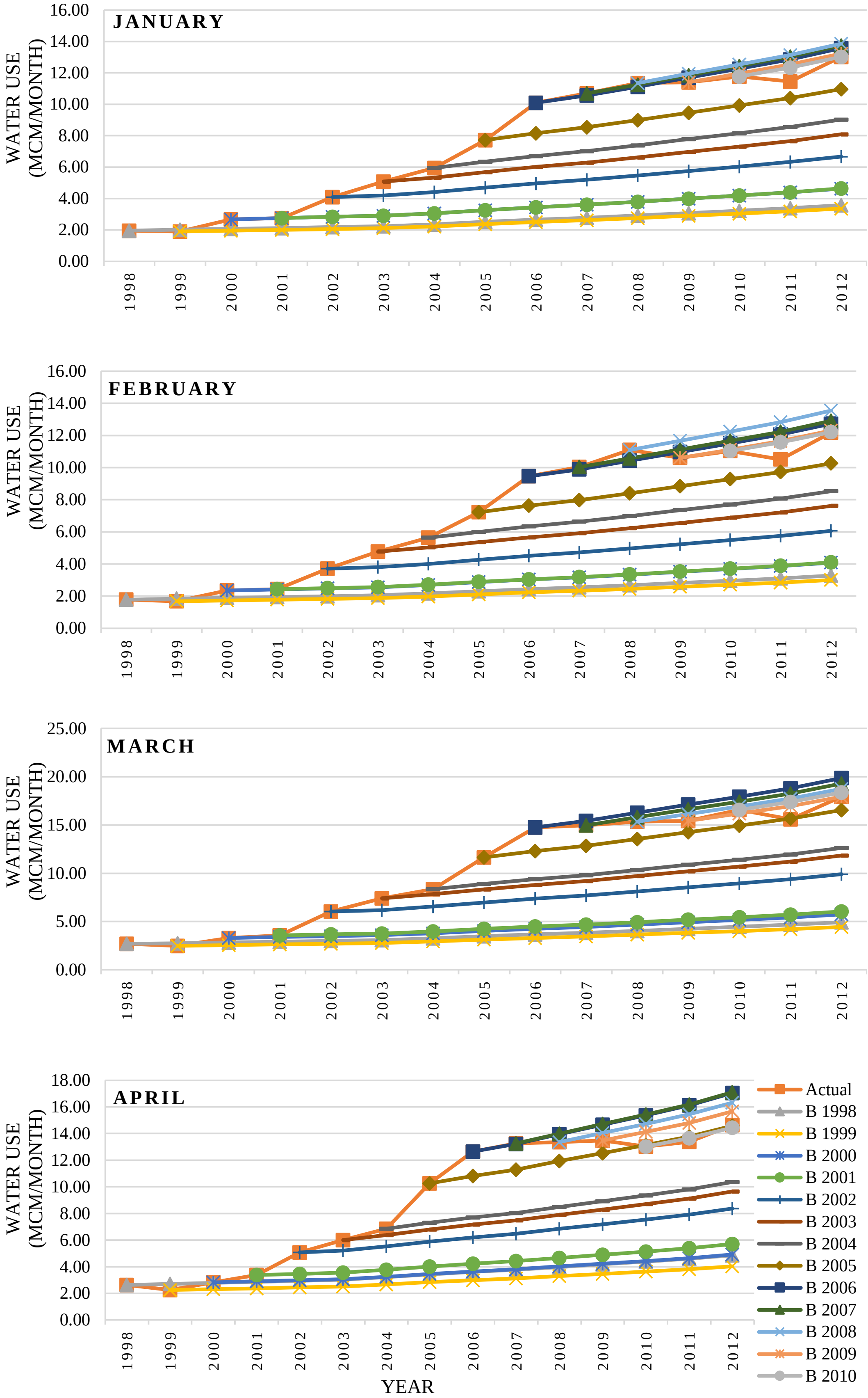


Figure 16: Actual and simulated monthly water use for residential sector using model 1

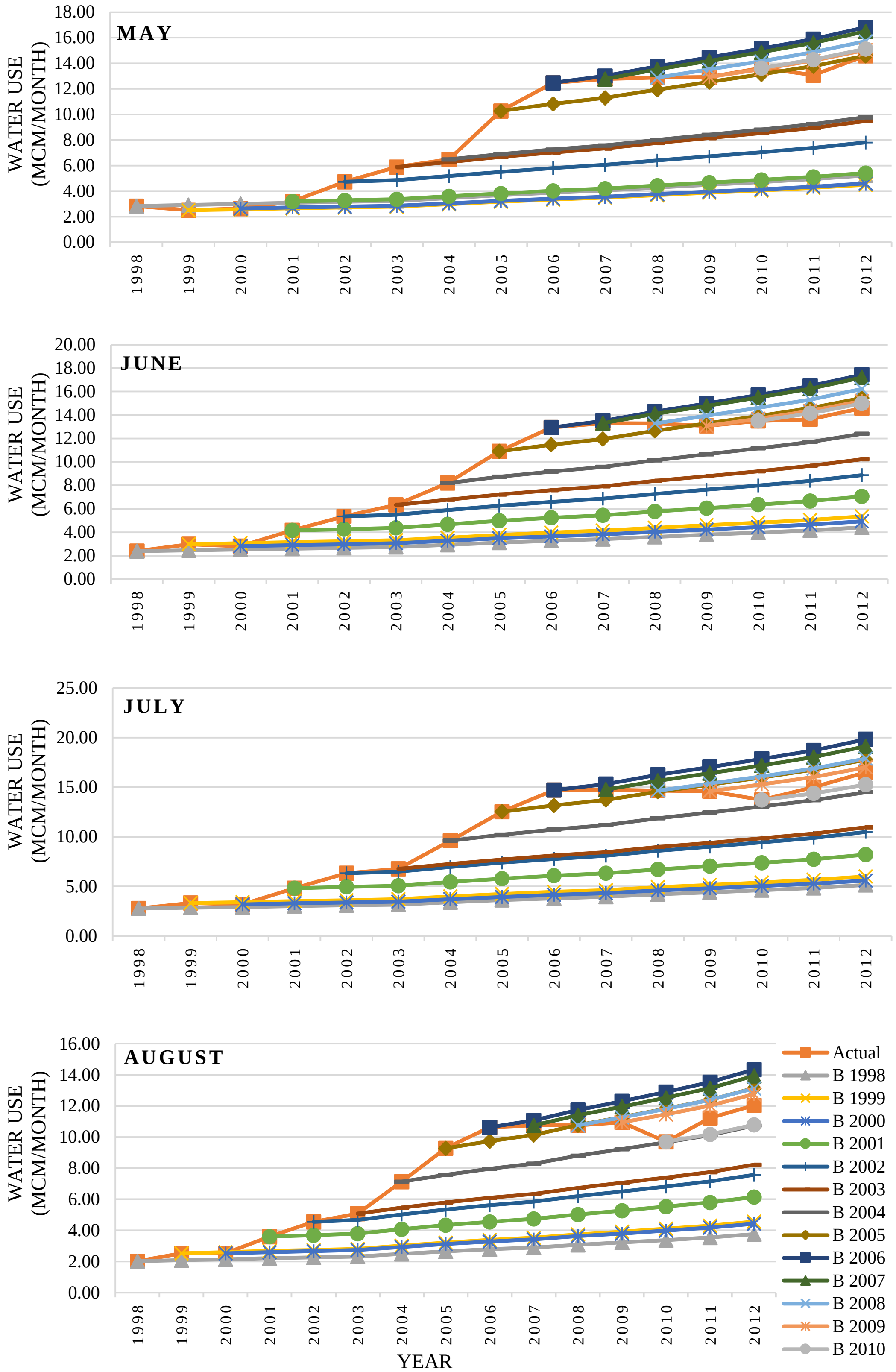


Figure 16: Actual and simulated monthly water use for residential sector using model 1

(Continued)

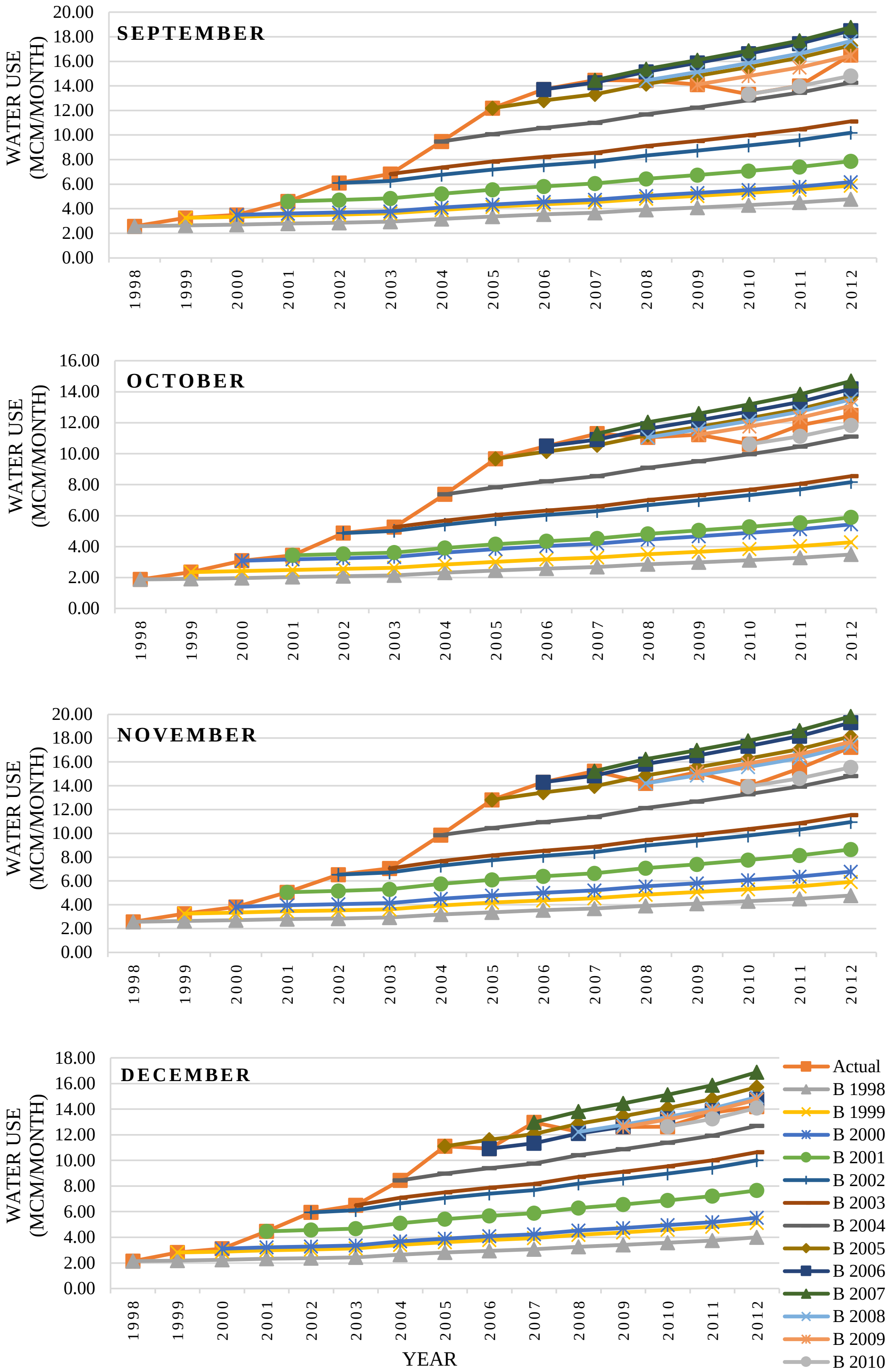


Figure 16: Actual and simulated monthly water use for residential sector using model 1

(Continued)

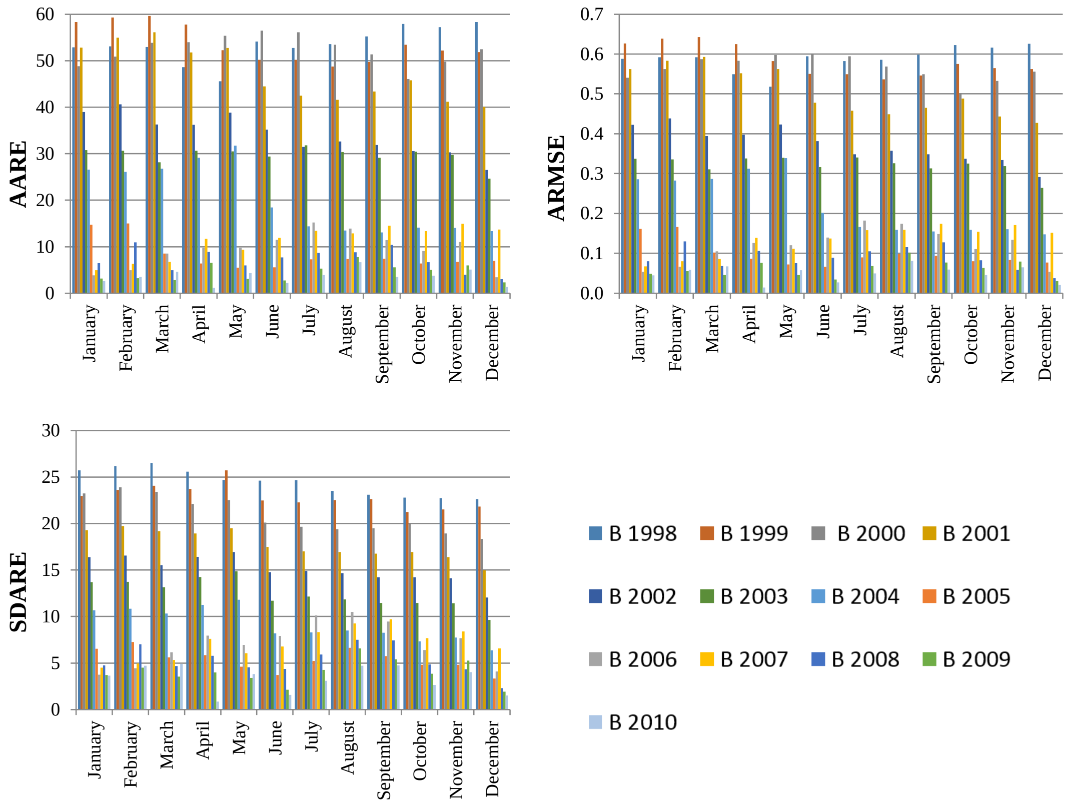


Figure 17: Error values of all calibration simulations for residential sector (database 4) using model 1

5.1.4.3 Non-metered Services Sector

Figure 18 shows the calibration simulations for non-metered services (services do not have a water meter to measure usage) with different base years. It shows that the highest and lowest actual consumption are observed in year 2012 in months of August (average temperature is 37°C) and February (average temperature is 21°C), respectively (AADC, 2015). Figure 19 represents the calculated AARE, ARMSE, and SDARE for all calibration simulations. The results concluded that year 2010 would be the best base year to forecast future demand in April, July, September, October, and December. Year 2009 would be the best for January, February, March, May, and June, while 2005 and 2008 would be the best for August and November, respectively.

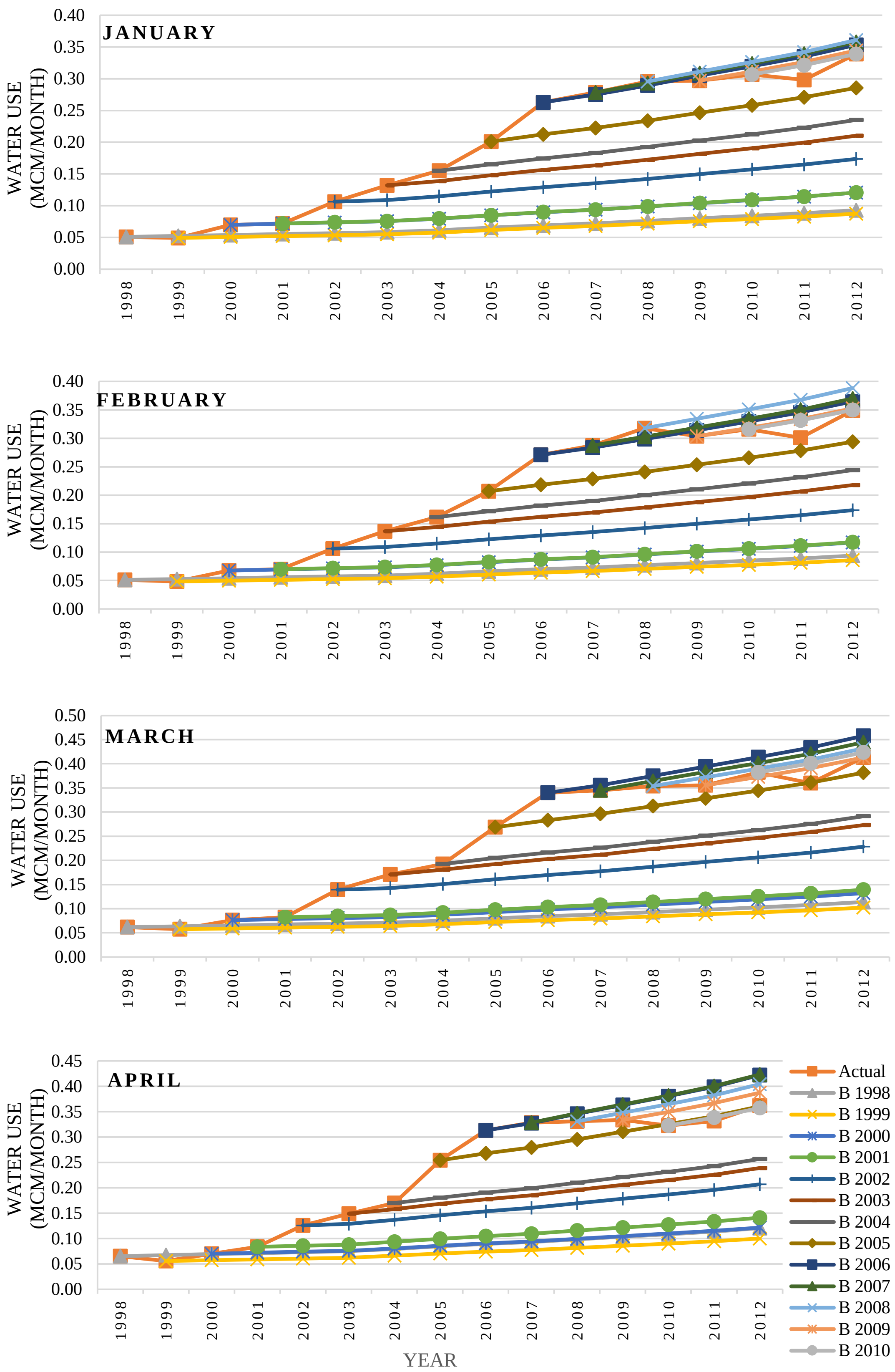


Figure 18: Actual and simulated monthly water use for non-metered services sector using model 1

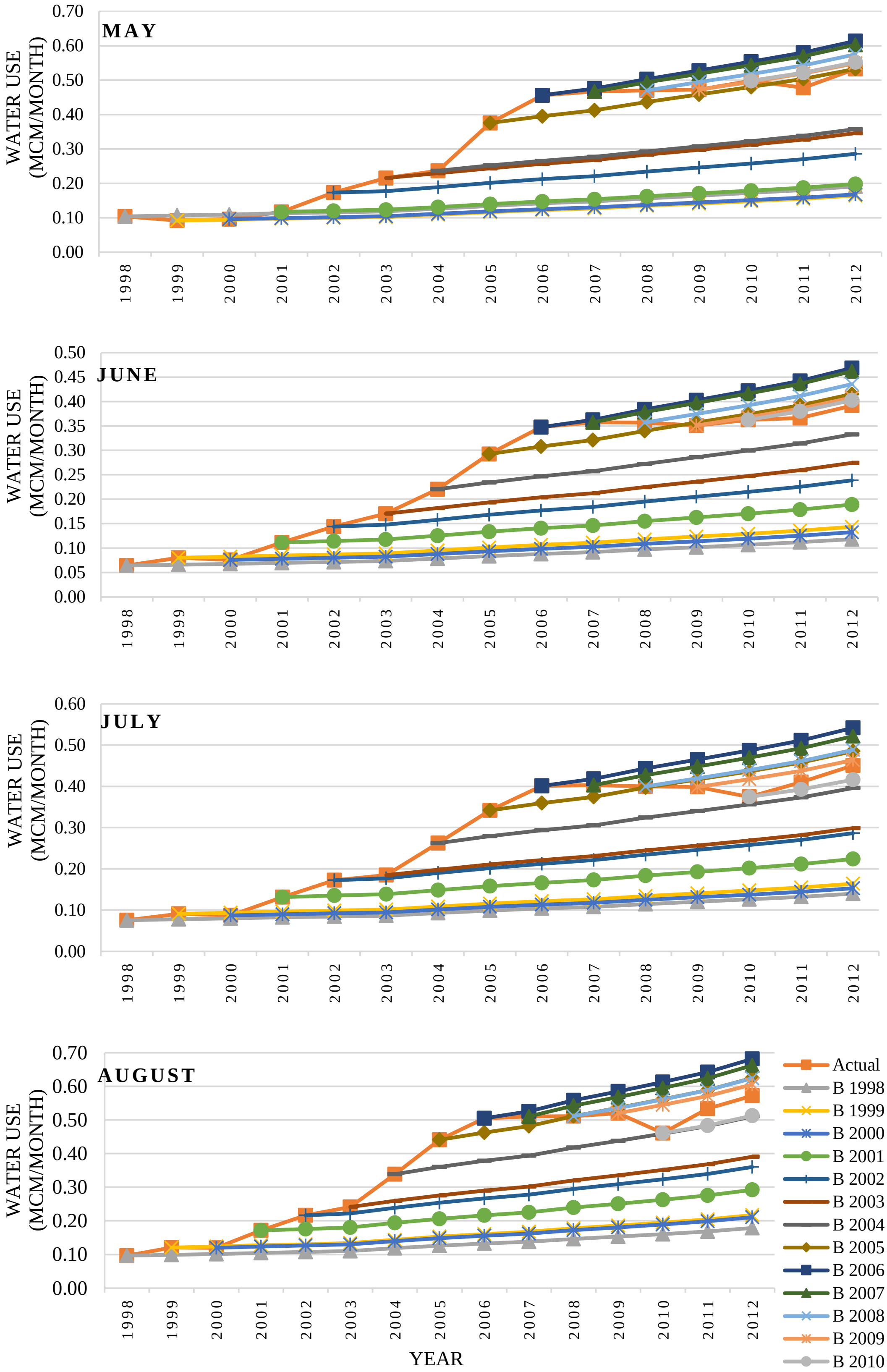


Figure 18: Actual and simulated monthly water use for non-metered services sector using model 1 (Continued)

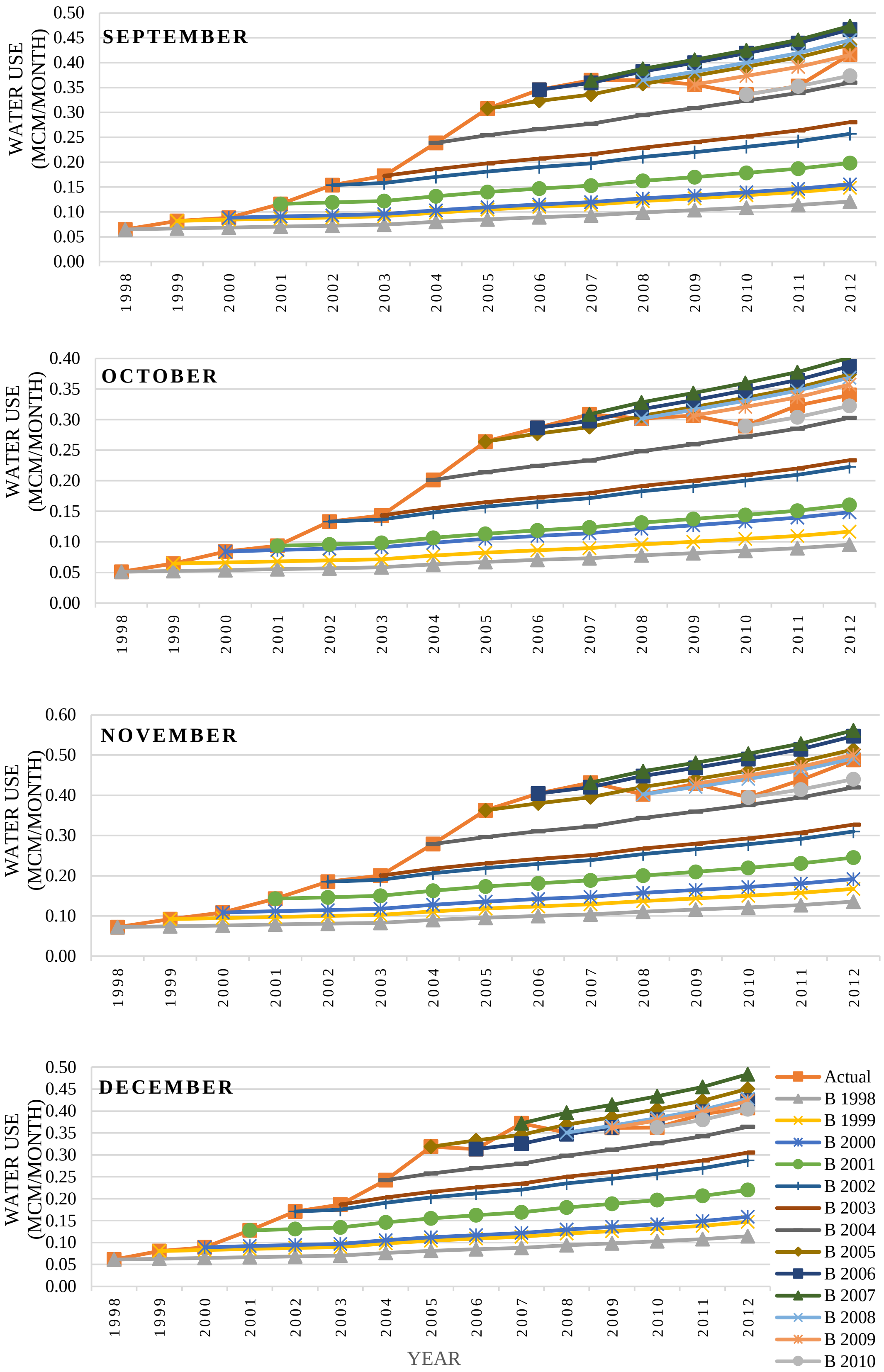


Figure 18: Actual and simulated monthly water use for non-metered services sector using model 1 (Continued)

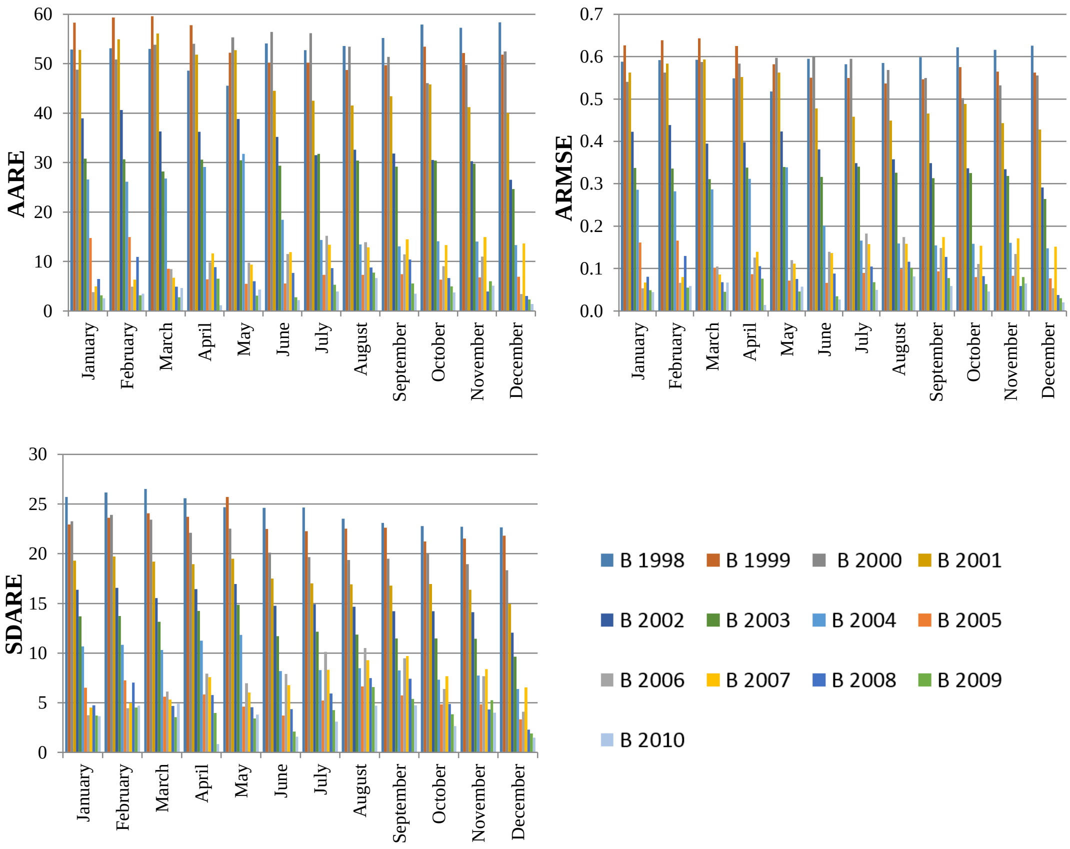


Figure 19: Error values of all calibration simulations for non-metered services sector (database 4) using model 1

5.1.4.4 Commercial Sector

Figure 20 shows the actual and calibrated monthly water use for commercial sector with different base years. The highest actual consumption is observed in August which has a high temperature (average of 37°C) in year 2012 and the lowest actual consumption is observed in February which has a low temperature (average of 21°C) in the same year (AADC, 2015). Figure 21 presents the calculated AARE, ARMSE, and SDARE for all calibration simulations. It shows that the base year 2010 is selected for April, July, September, October, and December. While, year 2009 would be the best base year for January, February, March, May, and June. Years 2005 and 2008 would be the best for August and November, respectively.

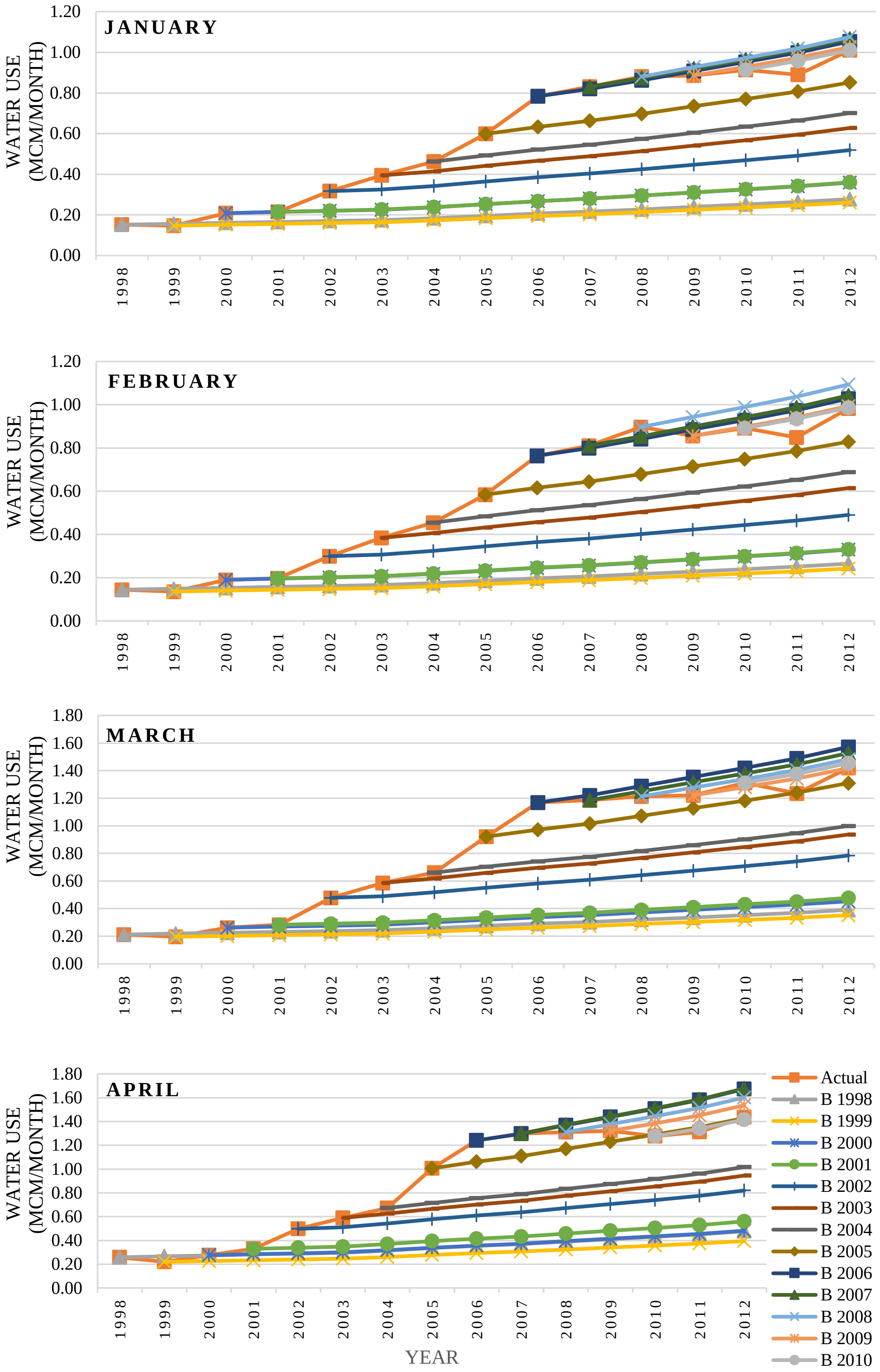


Figure 20: Actual and simulated monthly water use for commercial sector using model 1

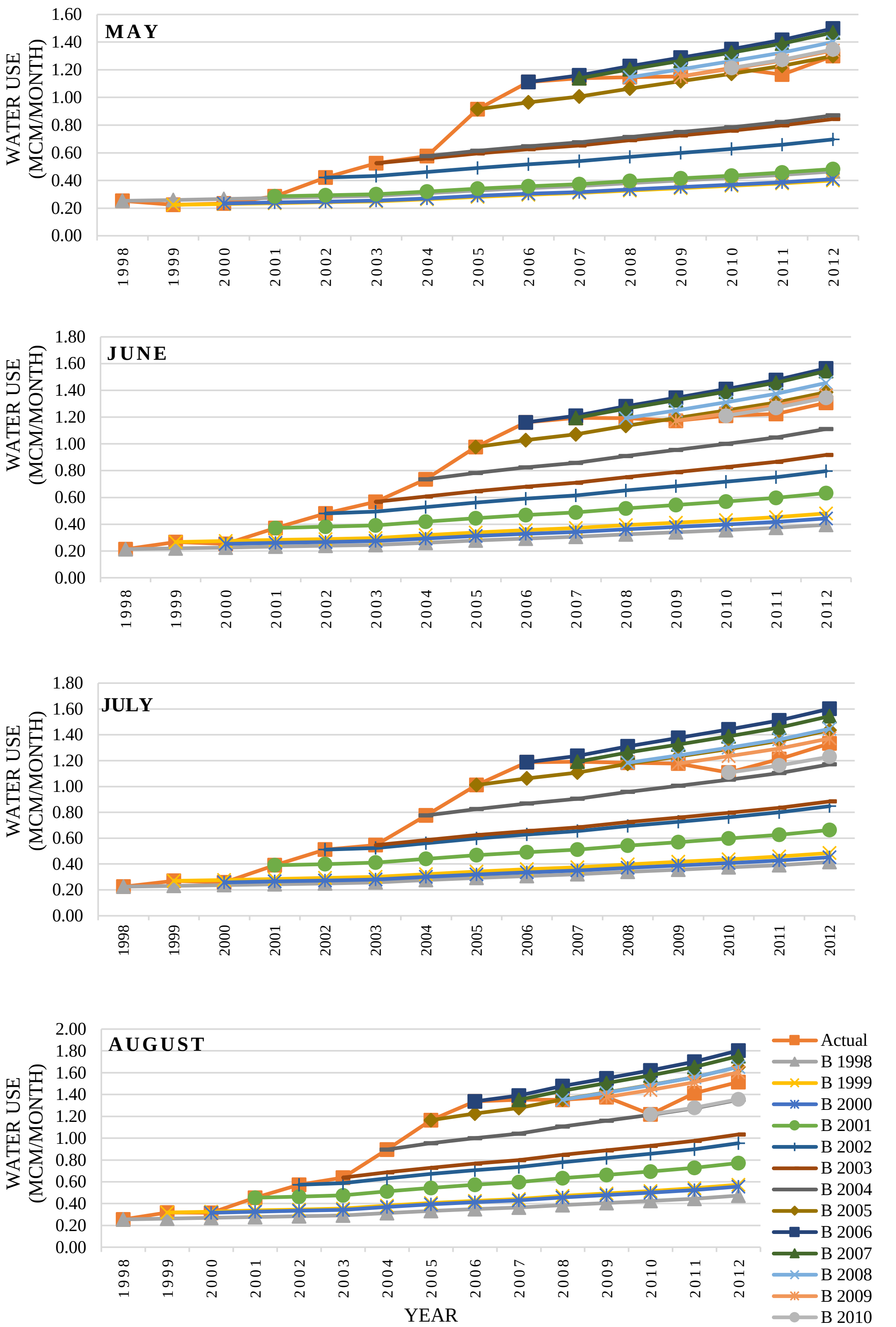


Figure 20: Actual and simulated monthly water use for commercial sector using model 1

(Continued)

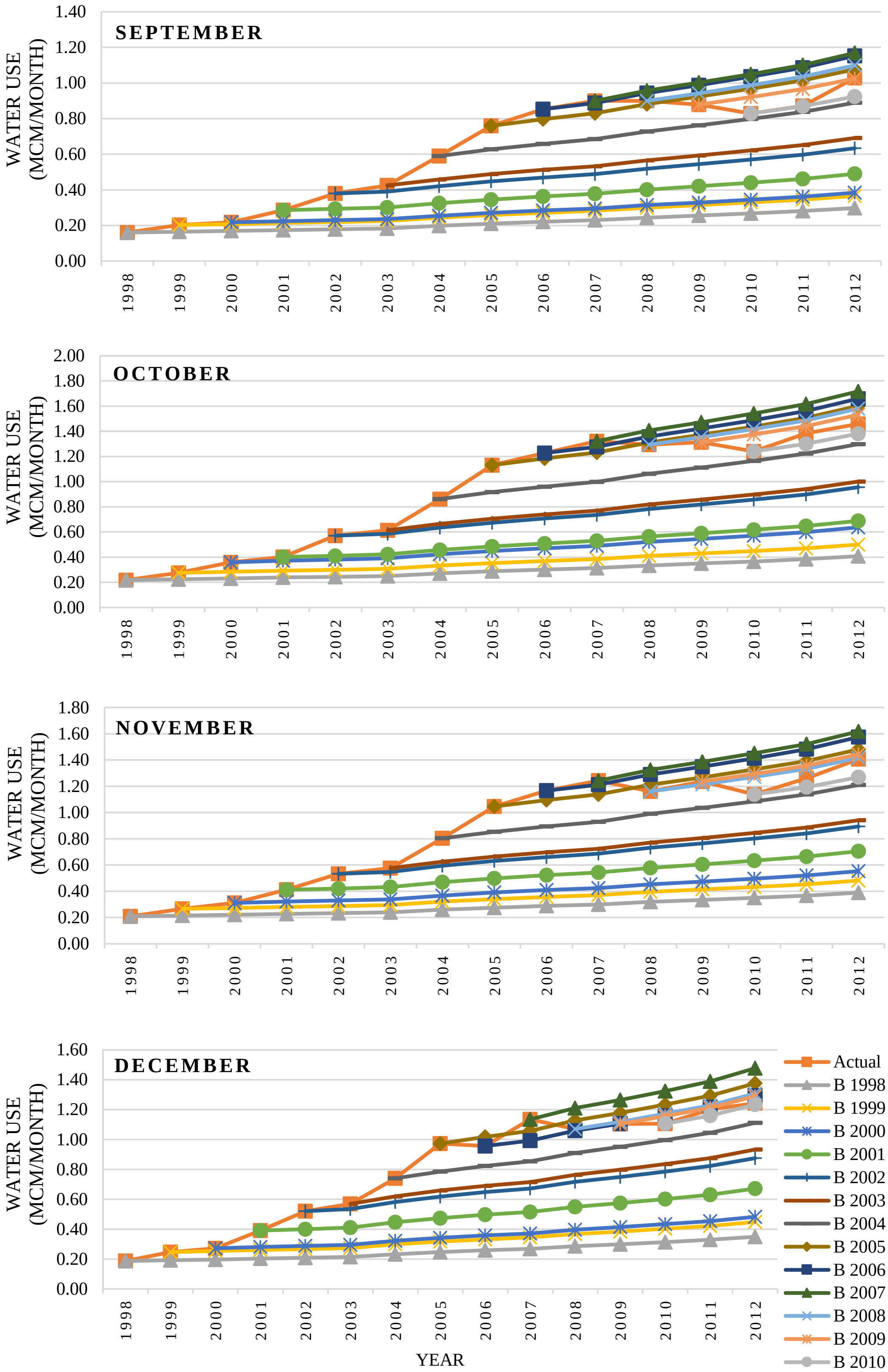


Figure 20: Actual and simulated monthly water use for commercial sector using model 1

(Continued)

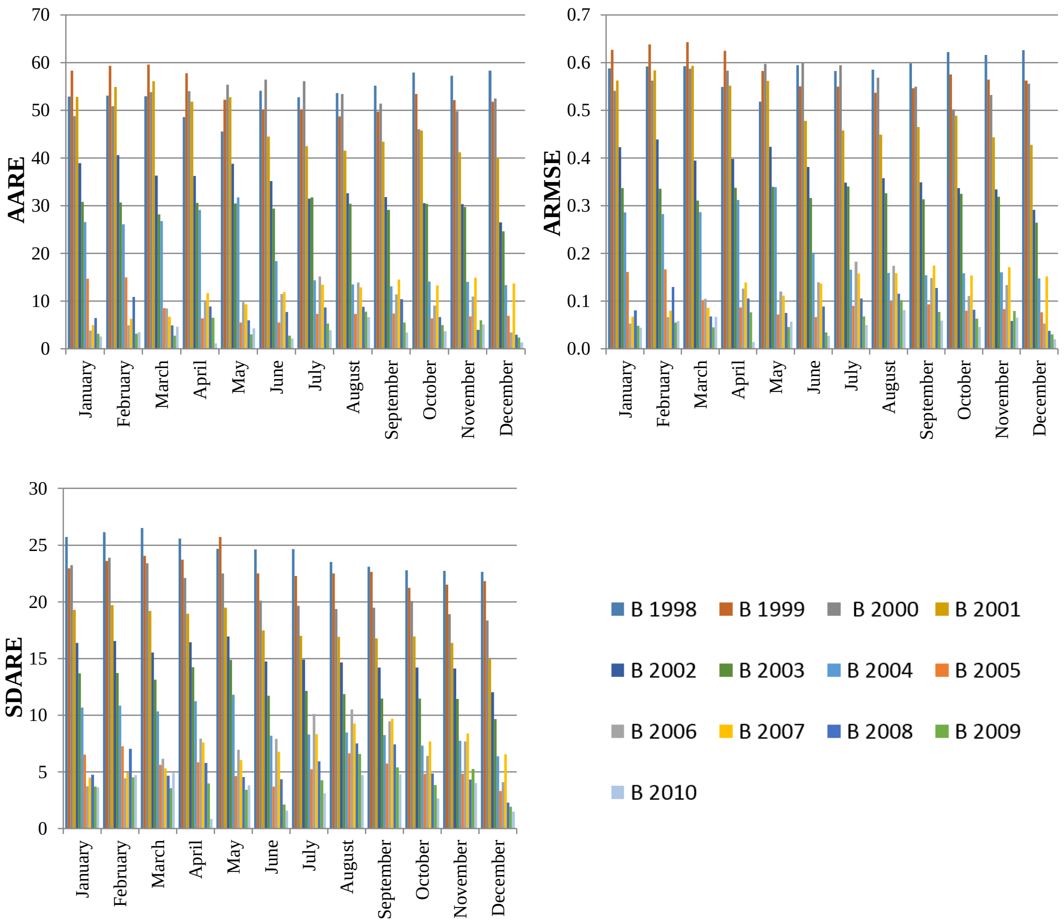


Figure 21: Error values of all calibration simulations for commercial sector (database 4) using model 1

5.1.4.5 Government Sector

Figure 22 displays the actual and simulated water use for government sector. In year 2012, the actual consumption is observed in August (average temperature is 37°C) and the lowest actual consumption is observed in March (average temperature is 24°C) (AADC, 2015). Figure 23 shows the values of AARE, ARMSE, and SDARE for all calibration simulations. Year 2010 would be the best base year to forecast future demand in April, July, September, October, and December. While, year 2009 would be the best base year for January, February, March, May, and June. Years 2005 and 2008 would be the best for August and November, respectively.

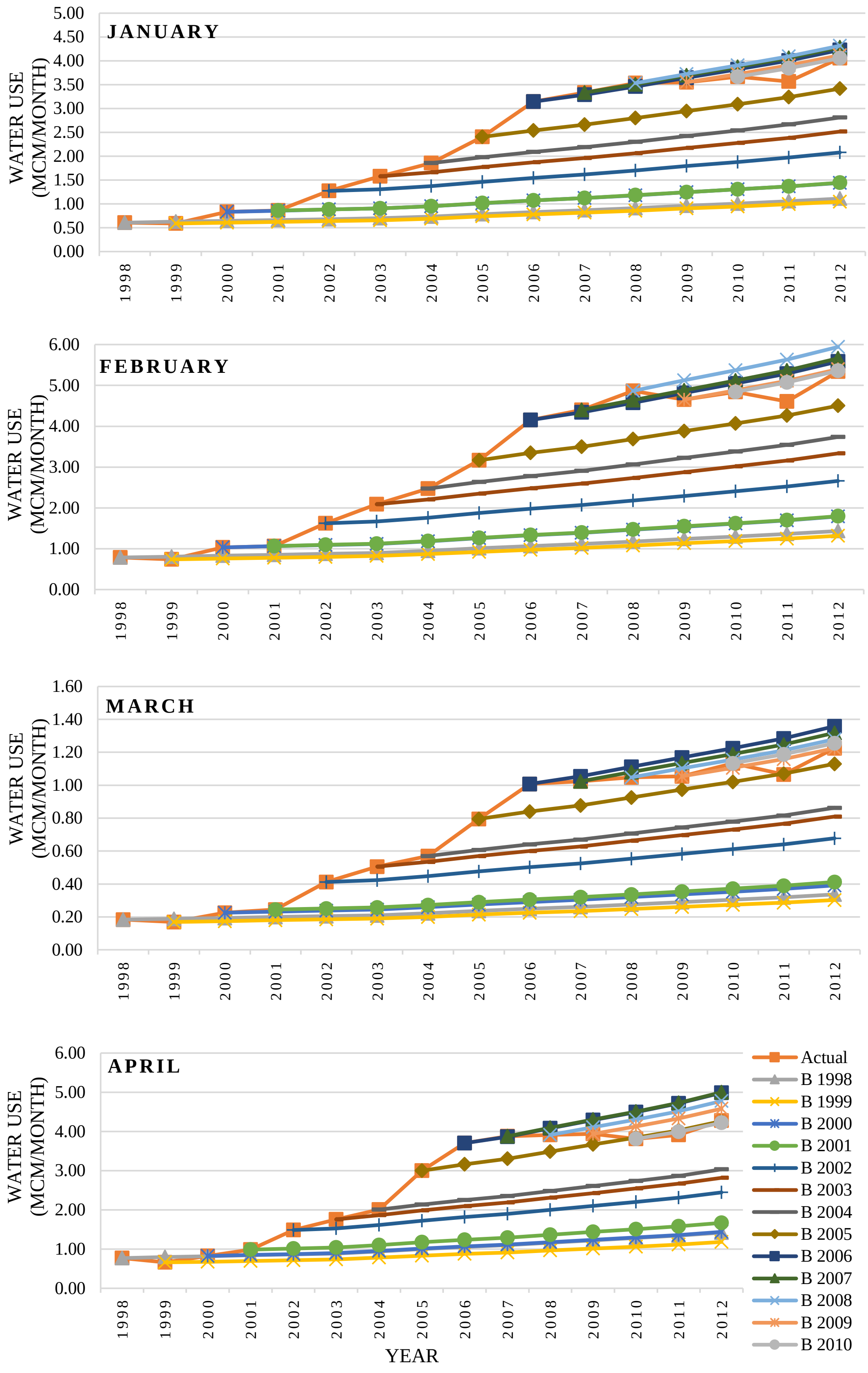


Figure 22: Actual and simulated monthly water use for government sector using model 1

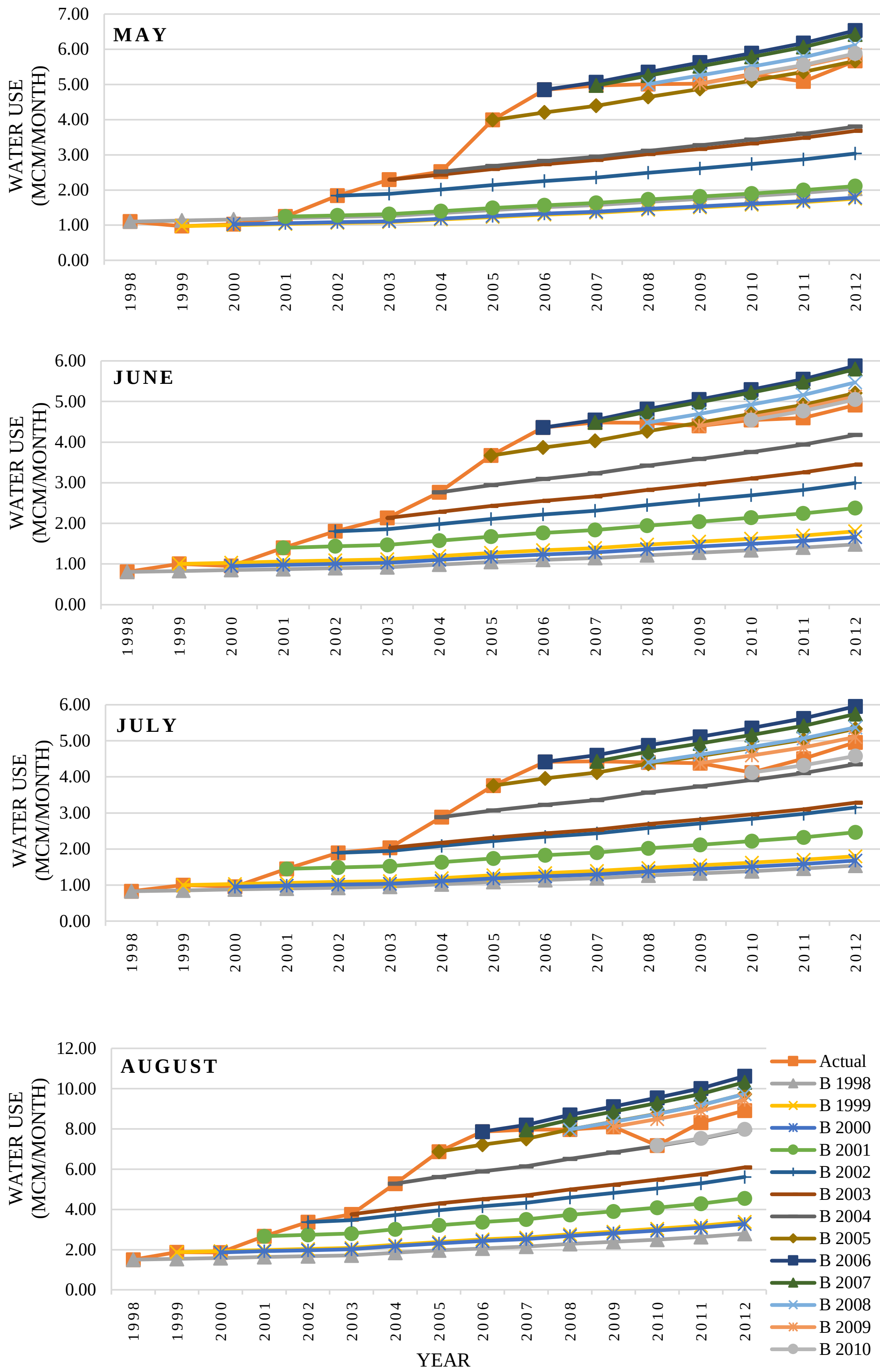


Figure 22: Actual and simulated monthly water use for government sector using model 1

(Continued)

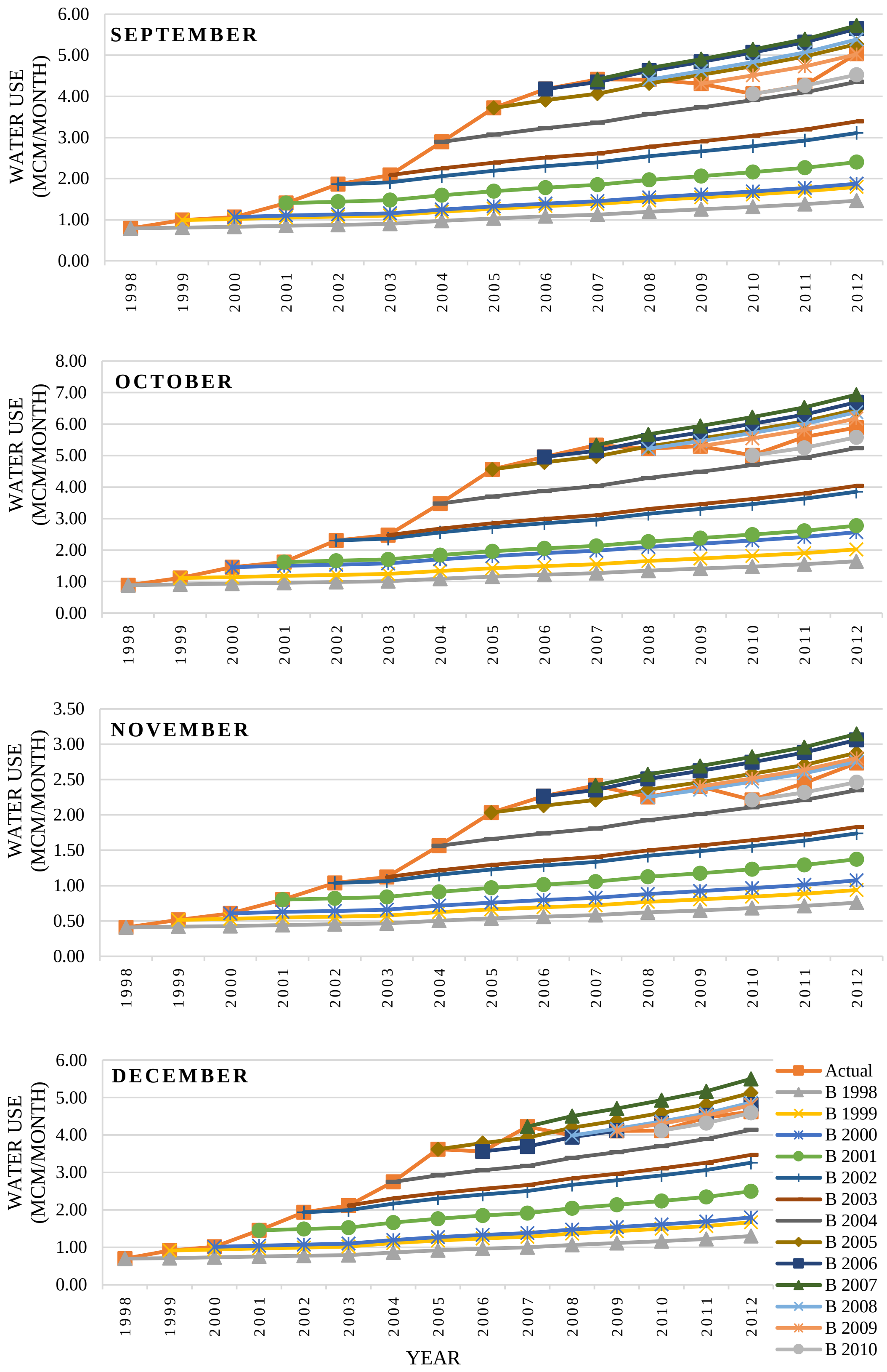


Figure 22: Actual and simulated monthly water use for government sector using model 1

(Continued)

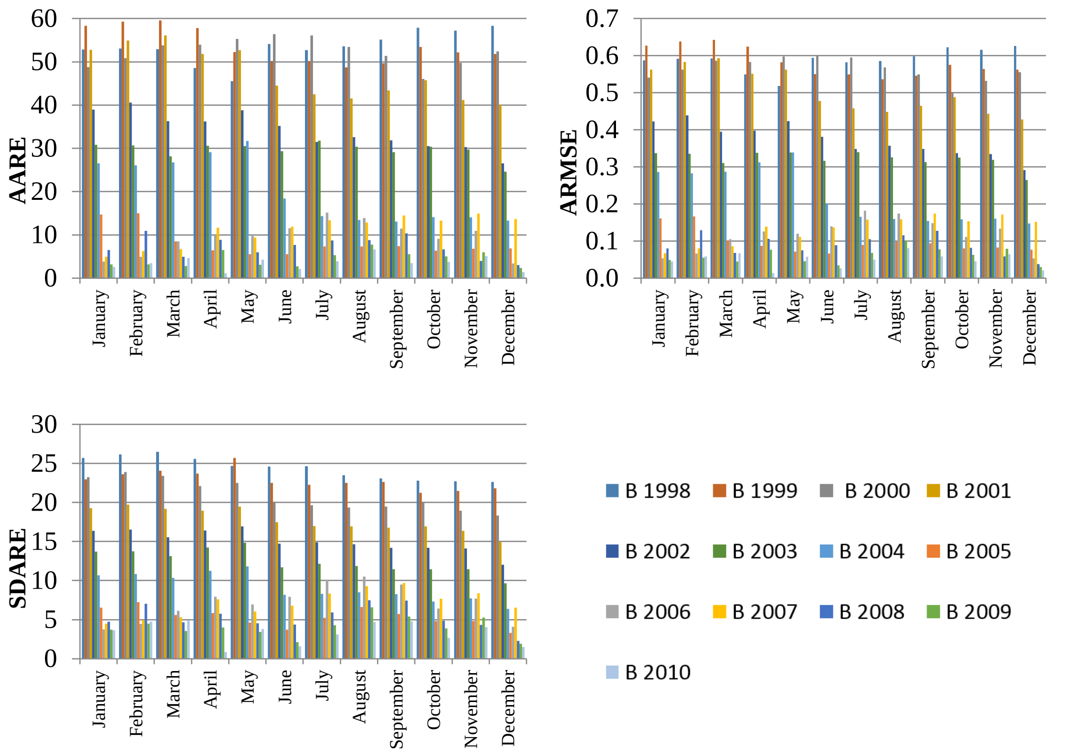


Figure 23: Error values of all calibration simulations for government sector (database 4) using model 1

5.1.4.6 Industrial Sector

Figure 24 illustrates the actual and calibrated water demand for industrial sector for all months of the year with different base years. The highest actual consumption is observed in year 2012 in June which has a high temperature (average of 35°C) and scarce in precipitation (average of 0.0 mm), while the lowest actual consumption is observed in February (average temperature is 33°C and average precipitation is 4.3 mm) in the same year (AADC and SCAD, 2015). Figure 25 presents the AARE, ARMSE, and SDARE for each month for the different base years. The base year 2010 is selected for April, July, September, October, and December. The base year 2009 is selected for January, February, March, May, and June. While, the base years 2005 and 2008 are selected for August and November, respectively.

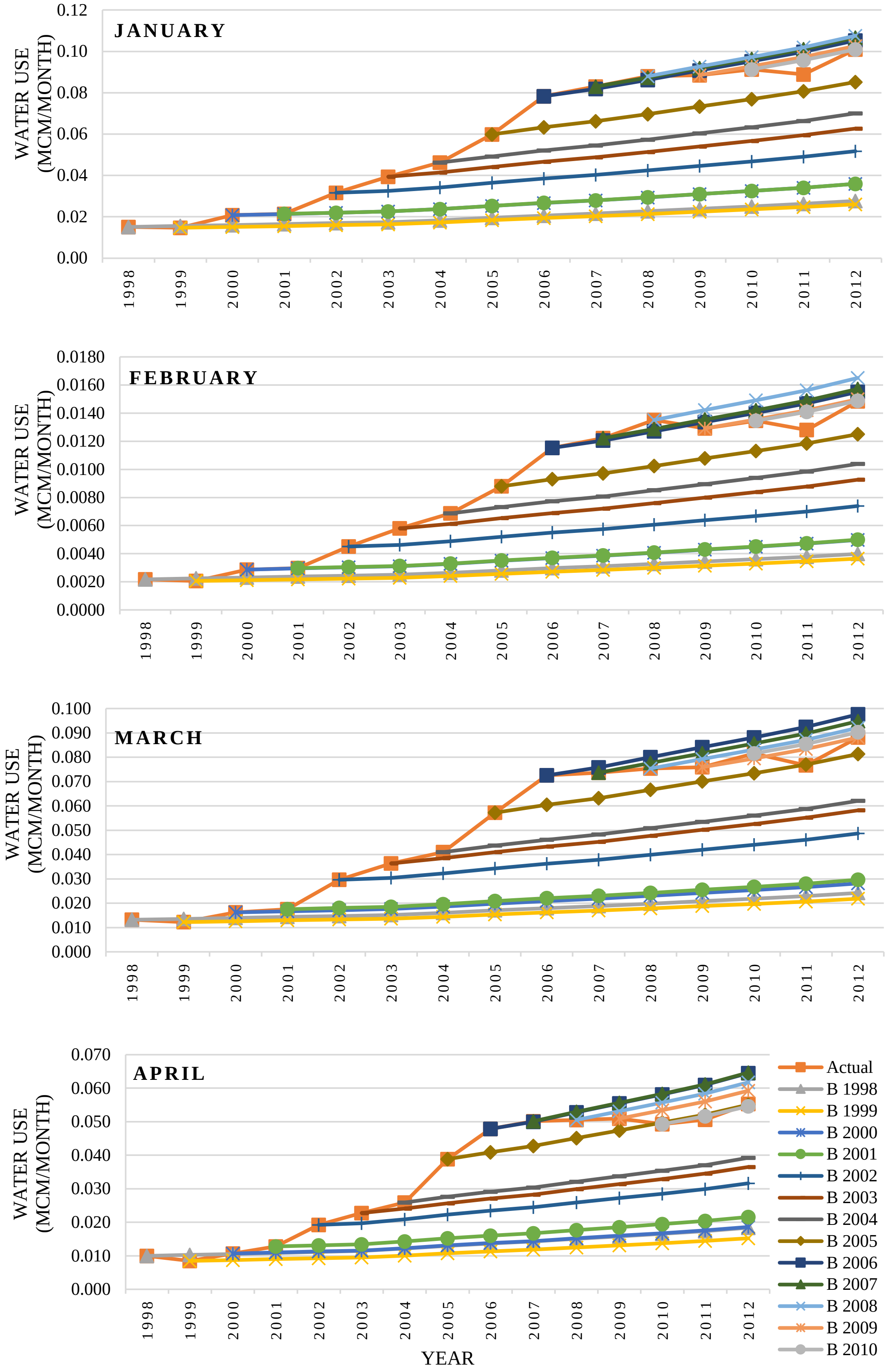


Figure 24: Actual and simulated monthly water use for industrial sector using model 1

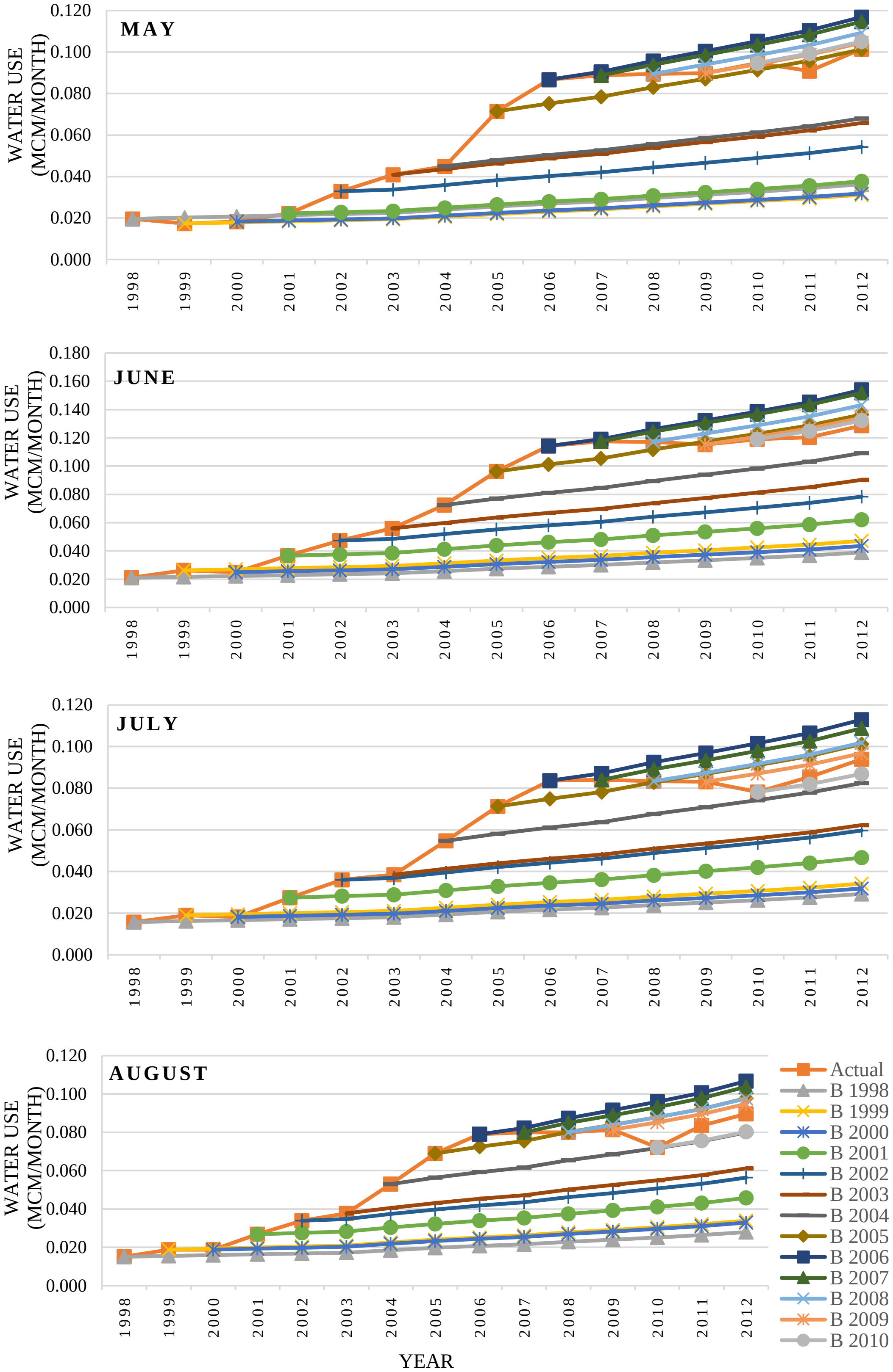


Figure 24: Actual and simulated monthly water use for industrial sector using model 1

(Continued)

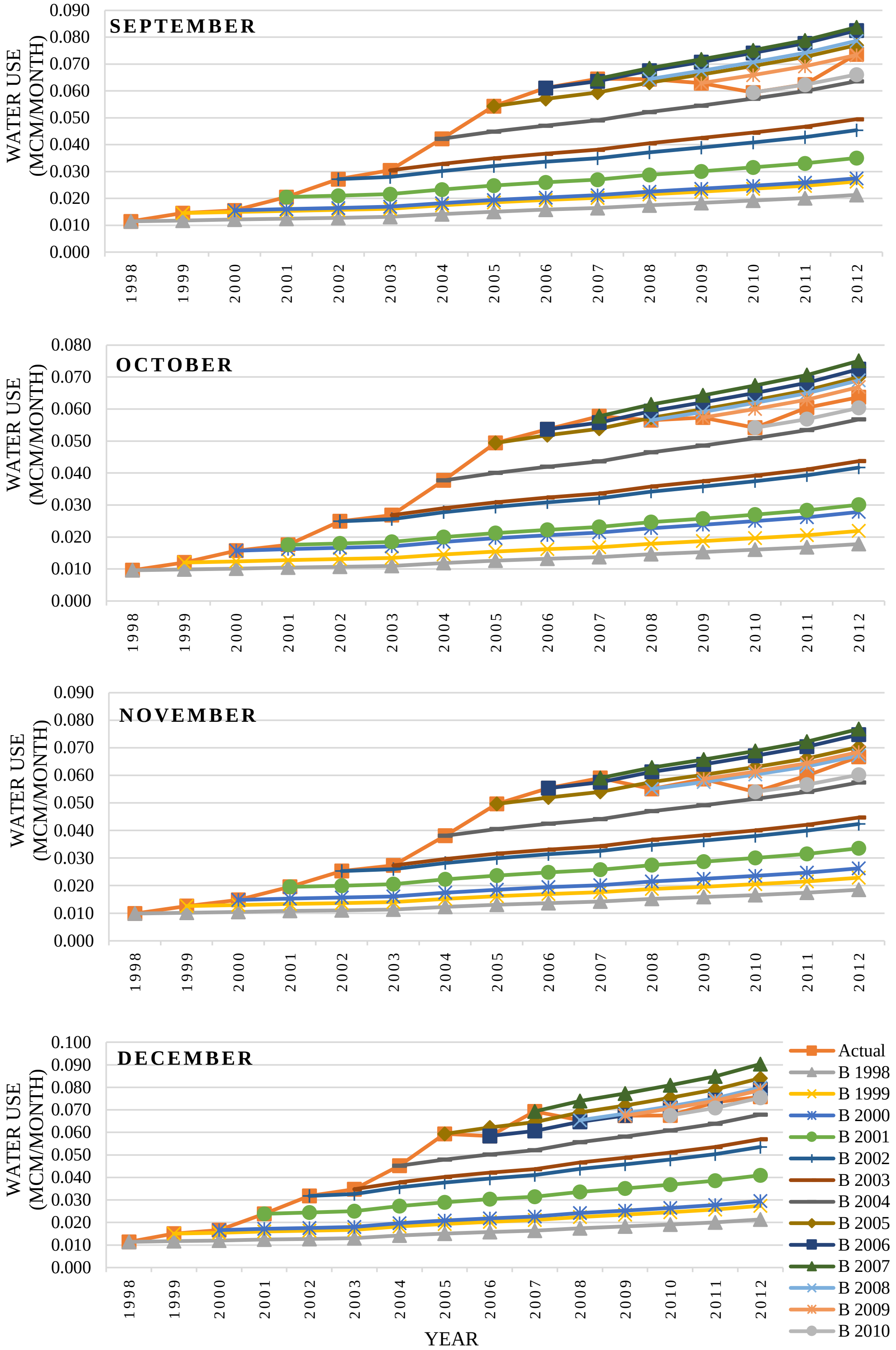


Figure 24: Actual and simulated monthly water use for industrial sector using model 1

(Continued)

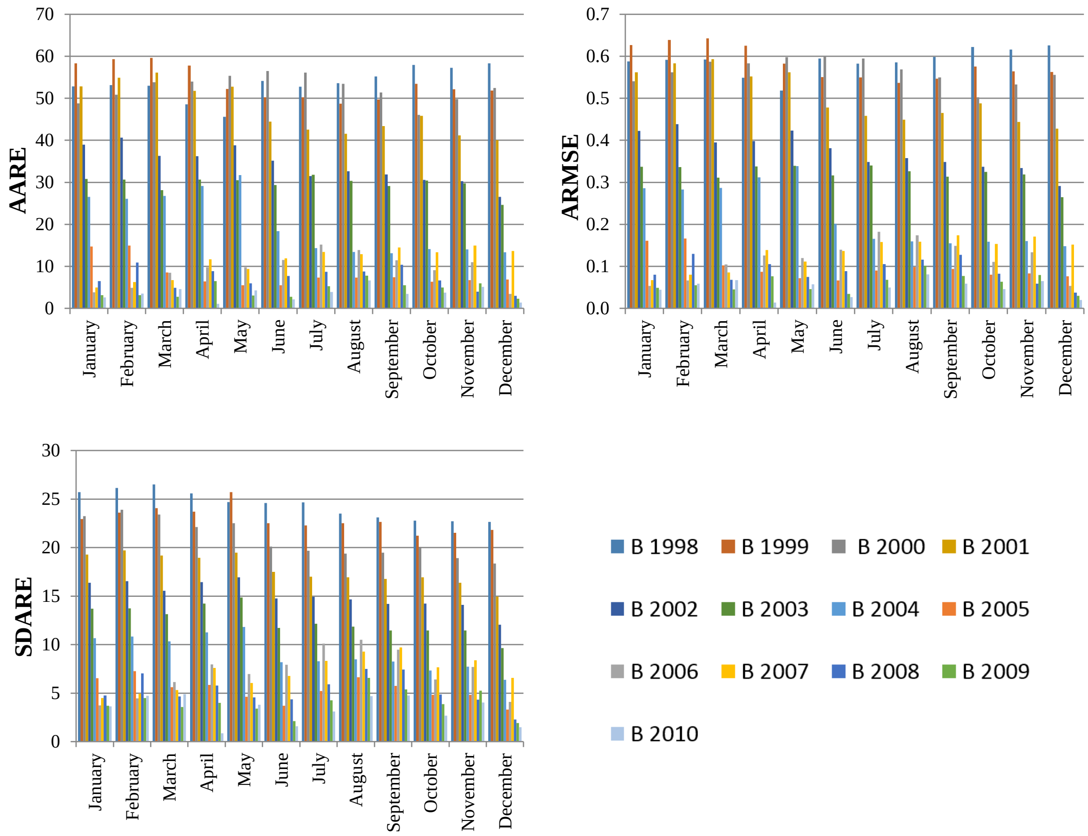


Figure 25: Error values of all calibration simulations for industrial sector (database 4) using model 1

5.1.4.7 Public Services Sector

Figure 26 presents the actual and calibrated water demand for public services sector with different base years. It shows that the highest and lowest actual consumption are observed in year 2012 in months of April (average temperature is 30°C) and February (average temperature is 21°C), respectively (AADC, 2015). Figure 27 shows the values of AARE, ARMSE, and SDARE for each month for the different base years. The base year 2010 is selected for April, July, September, October, and December. The base year 2009 is selected for January, February, March, May, and June. While, the base years 2005 and 2008 are selected for August and November, respectively.

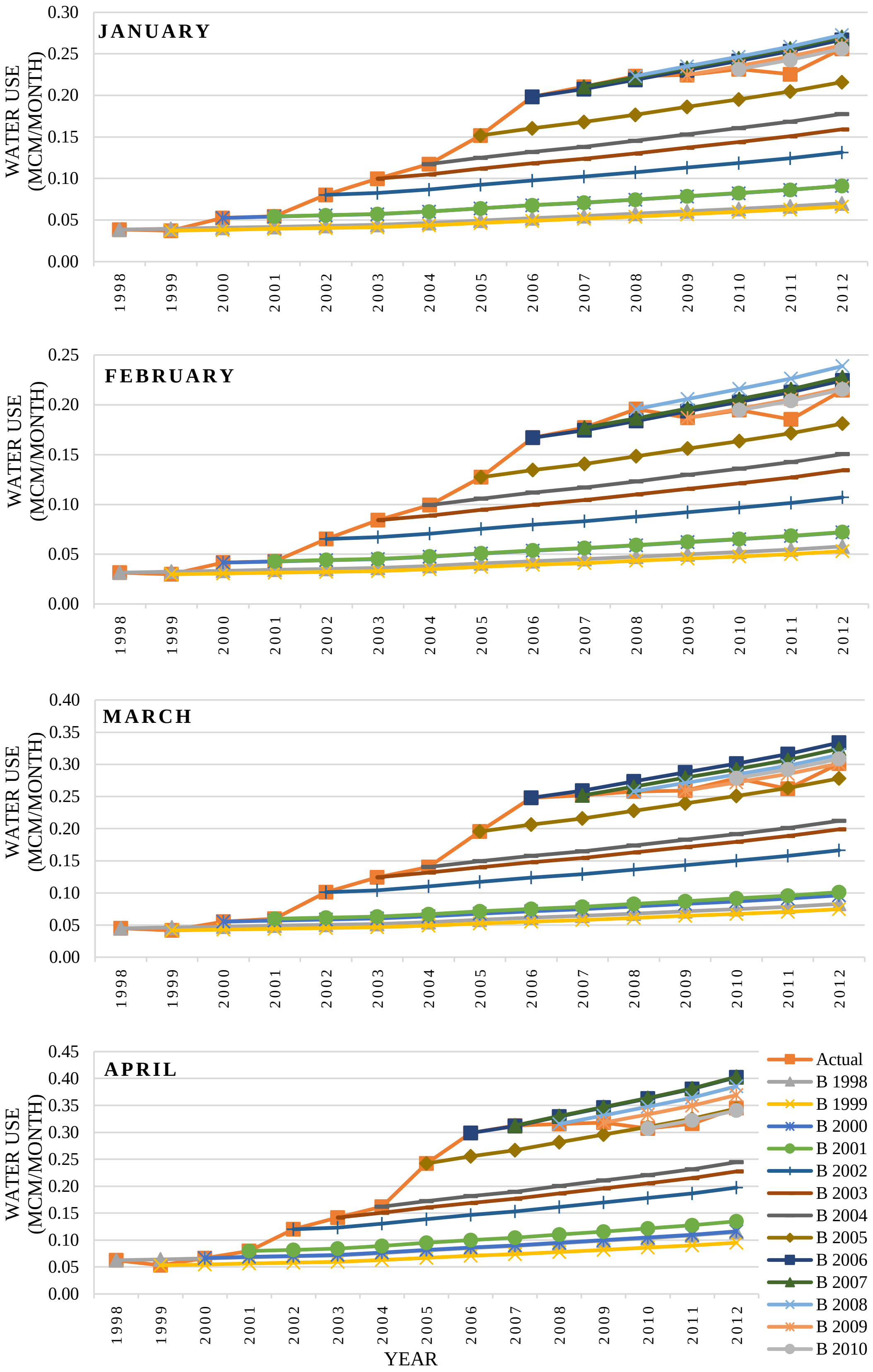


Figure 26: Actual and simulated monthly water use for public services sector using model 1

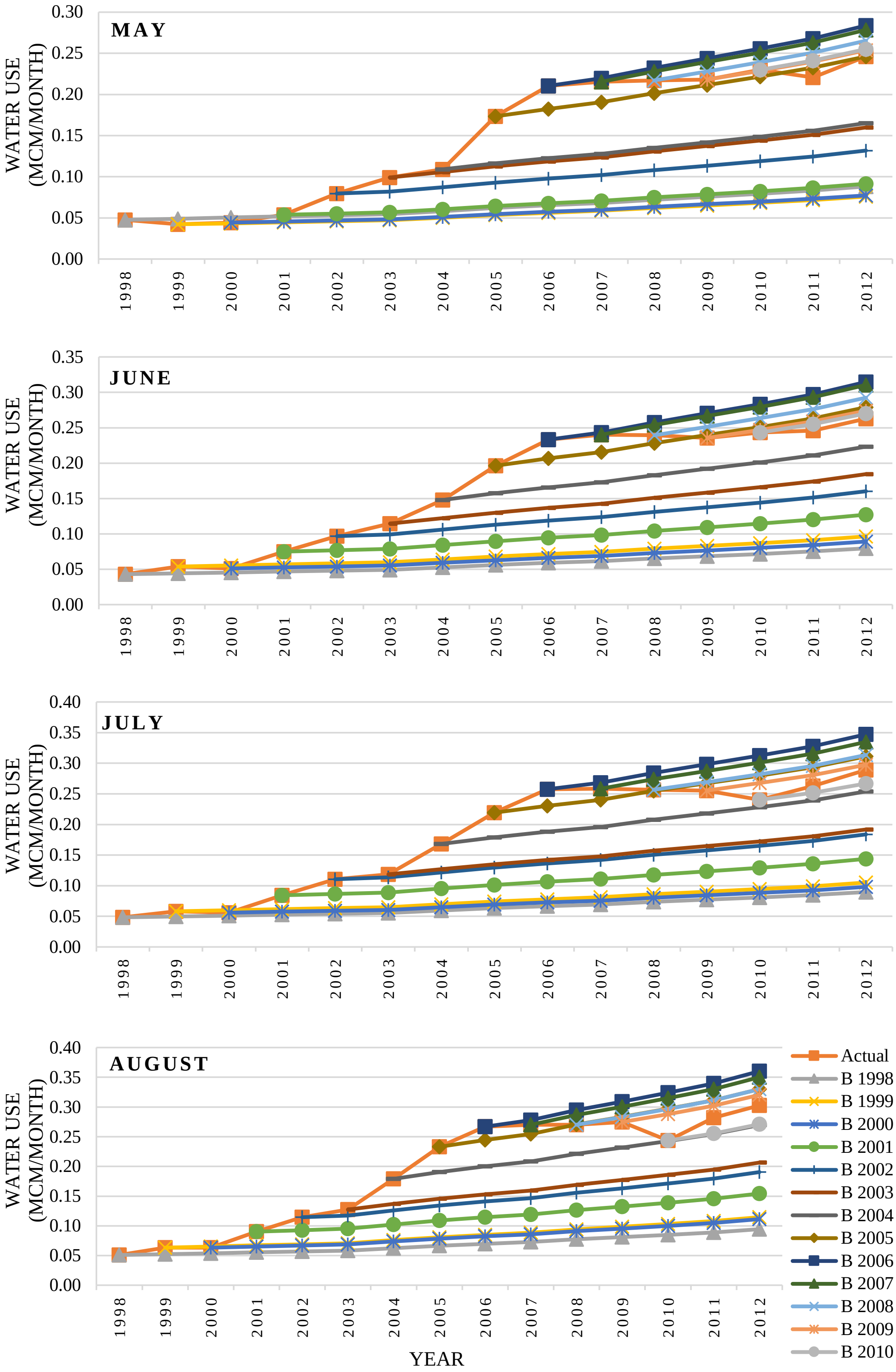


Figure 26: Actual and simulated monthly water use for public services sector using model 1

(Continued)

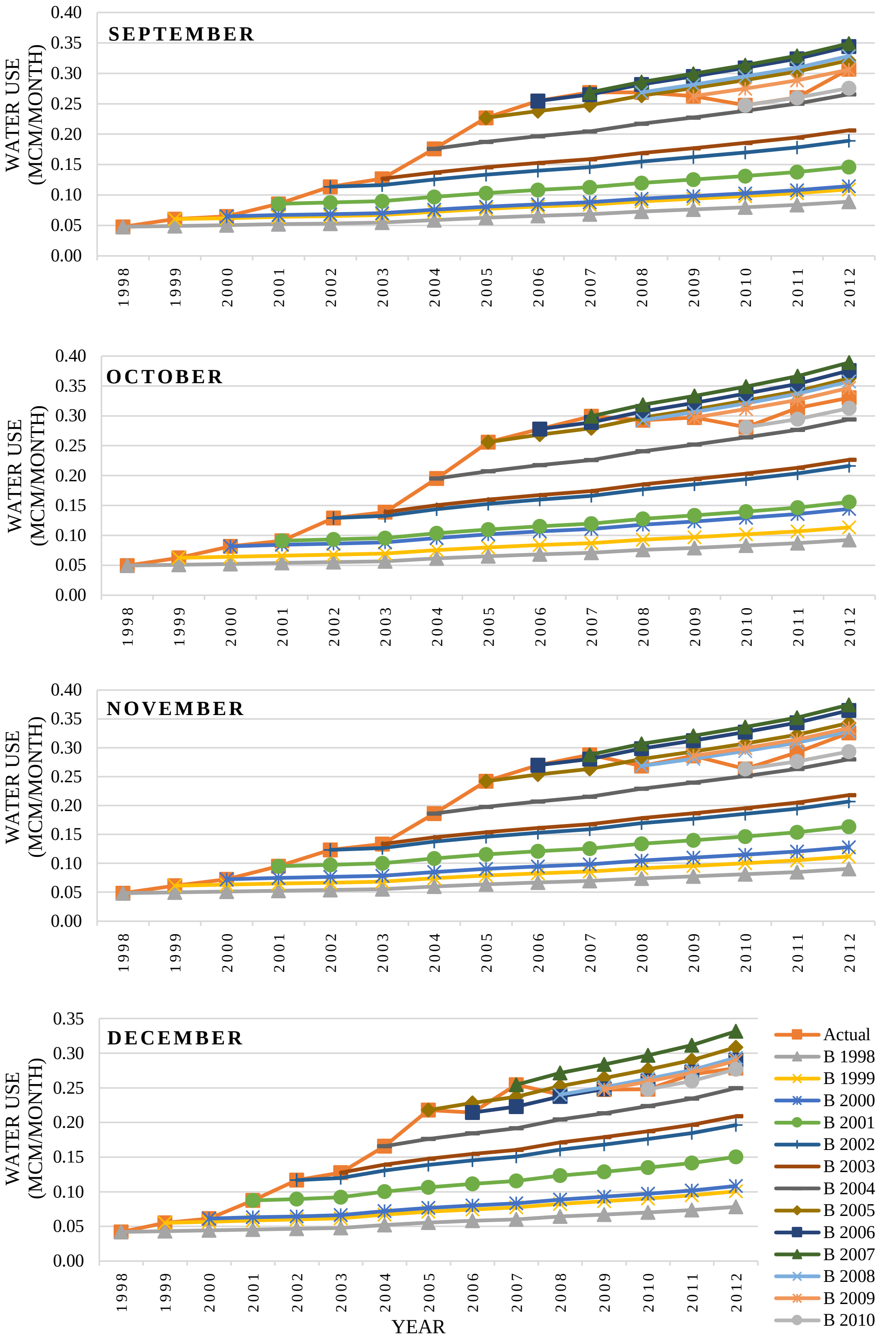


Figure 26: Actual and simulated monthly water use for public services sector using model 1

(Continued)

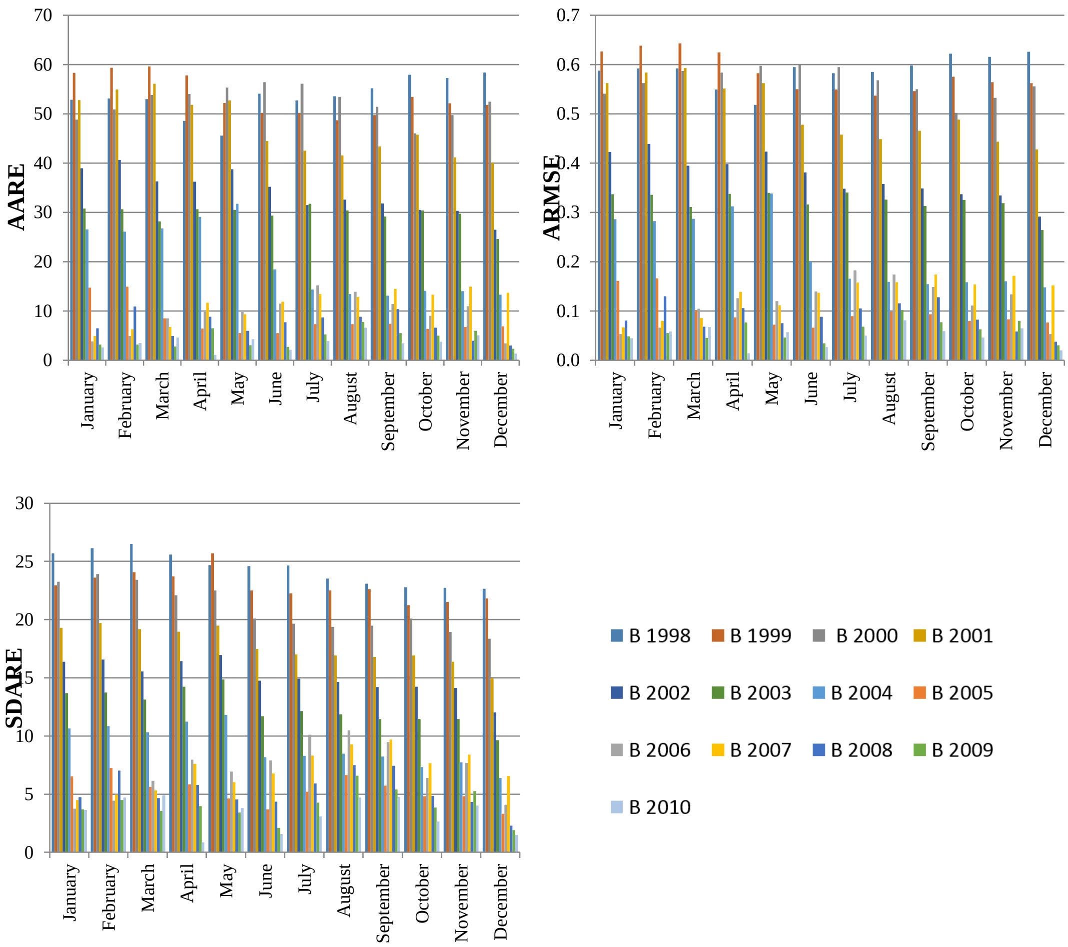


Figure 27: Error values of all calibration simulations for public services sector (database 4) using model 1

The calibration results of database 4 show that all sectors have the same base year. Table 20 summarizes the best base year for each month that will be considered for the forecasting scenarios.

Table 20: Best base year for database 4 using model 1

Month	Base year	Month	Base year
January	2009	July	2010
February	2009	August	2005
March	2009	September	2010
April	2010	October	2010
May	2009	November	2008
June	2009	December	2010

5.2 Calibration of Model 2: Linear Forecasting Model

This is the second model used in IWR-MAIN program and it estimates future water demand from using regression analysis. Basically, the equation of the linear forecasting model includes on the explanatory value, model intercept, and model coefficient for each variable (Eq. 8 in Chapter 3). In the following subsections, yearly and monthly data for water use are simulated for each water sector.

In the following subsections, database 1 represents data of total annual water use. Database 2 represents annual data of water use in each sector and database 3 represents data of total monthly water use in all sectors. However, database 4 represents monthly data of water use in each sector.

5.2.1 Database 1

Prior to using the program, the model explanatory coefficient and intercept are developed by SPSS. The only explanatory variable in this study is the population size of Al-Ain city. The intercept and coefficient (α, β) obtained from SPSS is shown in Table 21.

Table 21: Explanatory coefficient and intercept (β, α) for database 1

α	β
-16585.616457	0.122673

With linear forecasting model, the change in the estimated water use from year to year for various sectors are explained by changes in the explanatory variables. Thirteen simulations were performed with different base years in order to select the base year that presents water demand more accurately. Figure 28 illustrates the actual and simulated total water use during calibration period from 1998 to 2012 using database 1. The actual water consumption is generally increasing with time except in year 2010. The highest actual water use is encountered in year 2012. All calibration simulations are gradually increasing throughout the calibration period.

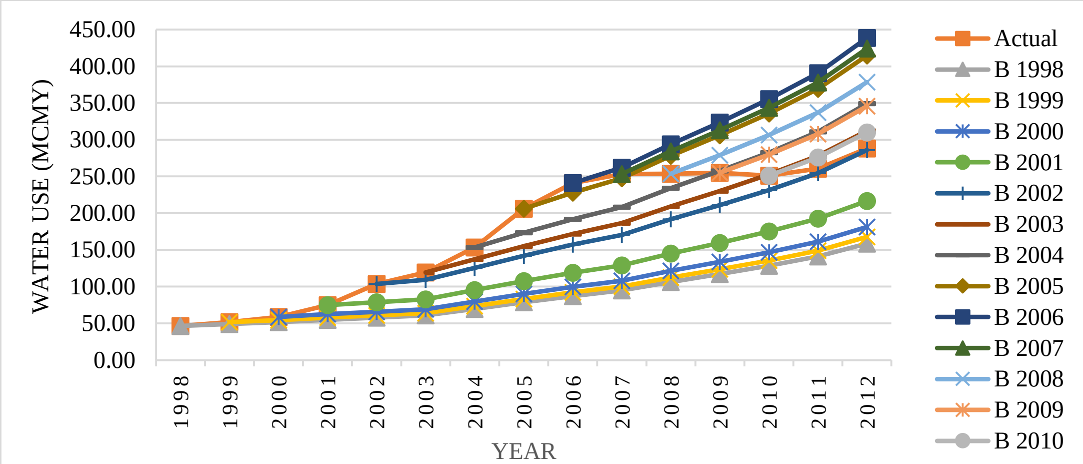
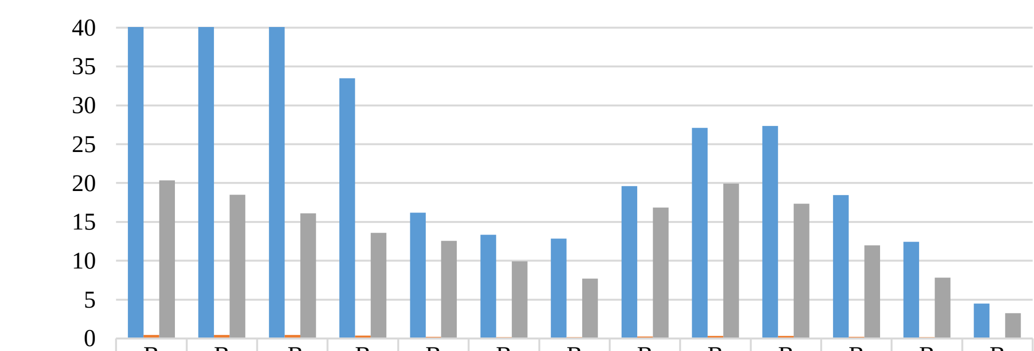


Figure 28: Actual and simulated total annual water use (database 1) using model 2

The average absolute relative error (AARE), the standard deviation of the absolute relative error (SDARE), and the average root mean square error (ARMSE) were calculated (Eq. 10 - 13) for each calibration simulation. Figure 29 presents the comparison between the actual and simulated water use for all selected base years.



	B 1998	B 1999	B 2000	B 2001	B 2002	B 2003	B 2004	B 2005	B 2006	B 2007	B 2008	B 2009	B 2010
AARE	42	42	41	33	16	13	13	20	27	27	18	12	4
ARMSE	0.5	0.5	0.4	0.4	0.2	0.2	0.1	0.3	0.3	0.3	0.2	0.1	0.1
SDARE	20	18	16	14	13	10	8	17	20	17	12	8	3

Figure 29: Error values of all calibration simulations for database 1 using model 2

Figure 29 shows that the error values are increased in later base years (2005 – 2008). This is because the actual water use has a fluctuation in the last years leaving a difference between the actual and simulated water use. The simulation of base year 2010 shows the lowest errors compared to other years. Based on the same criteria used in model 1, the calibration simulation with base year 2010 is selected in this model for database 1 to be used in forecasting scenarios.

5.2.2 Database 2

Data of annual water use for each sector is used in this section. The model intercept and coefficient (α, β) obtained from SPSS are shown in Table 8. Figure 30 illustrates the actual and simulated annual water use for each sector during calibration period from 1998 to 2012.

Table 22: Explanatory coefficients and intercepts (β, α) for database 2

Sector	α	β
Agricultural	-1471.001422	0.012221
Commercial	-871.930418	0.006554
Government	-3735.684941	0.025233
Industrial	-46.137323	0.000392
Non-metered Services	-305.656687	0.002179
Public Services	-210.610060	0.001492
Residential	-9939.744690	0.074593

Figure 30 shows that the highest water use is in residential sector; whereas, the lowest water use is in industrial sector. For later calibration period, the simulated water use is higher than the actual water use.

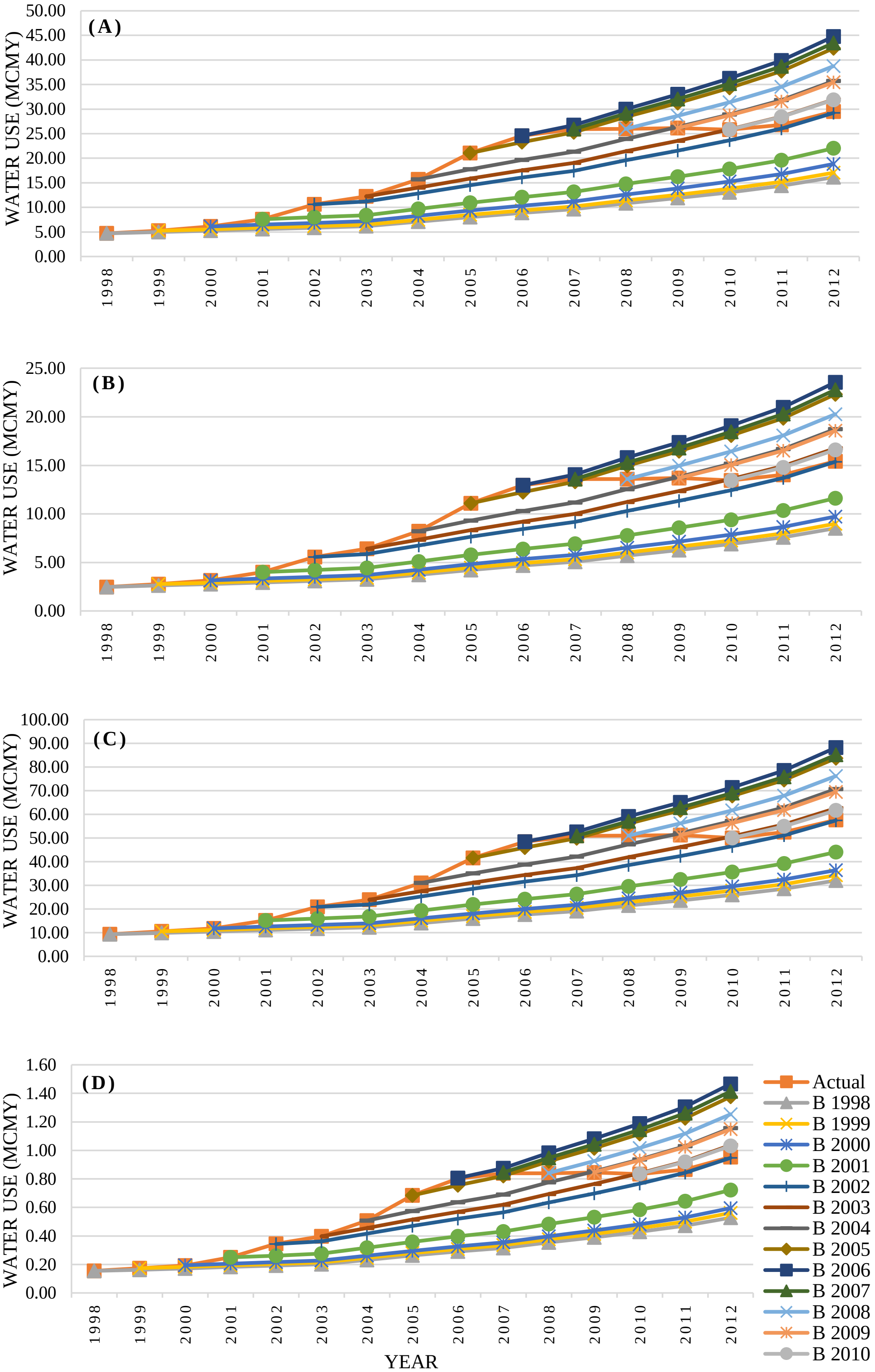


Figure 30: Actual and simulated total annual water use (database 2) using model 2 for (A) agricultural, (B) commercial, (C) government, and (D) industrial

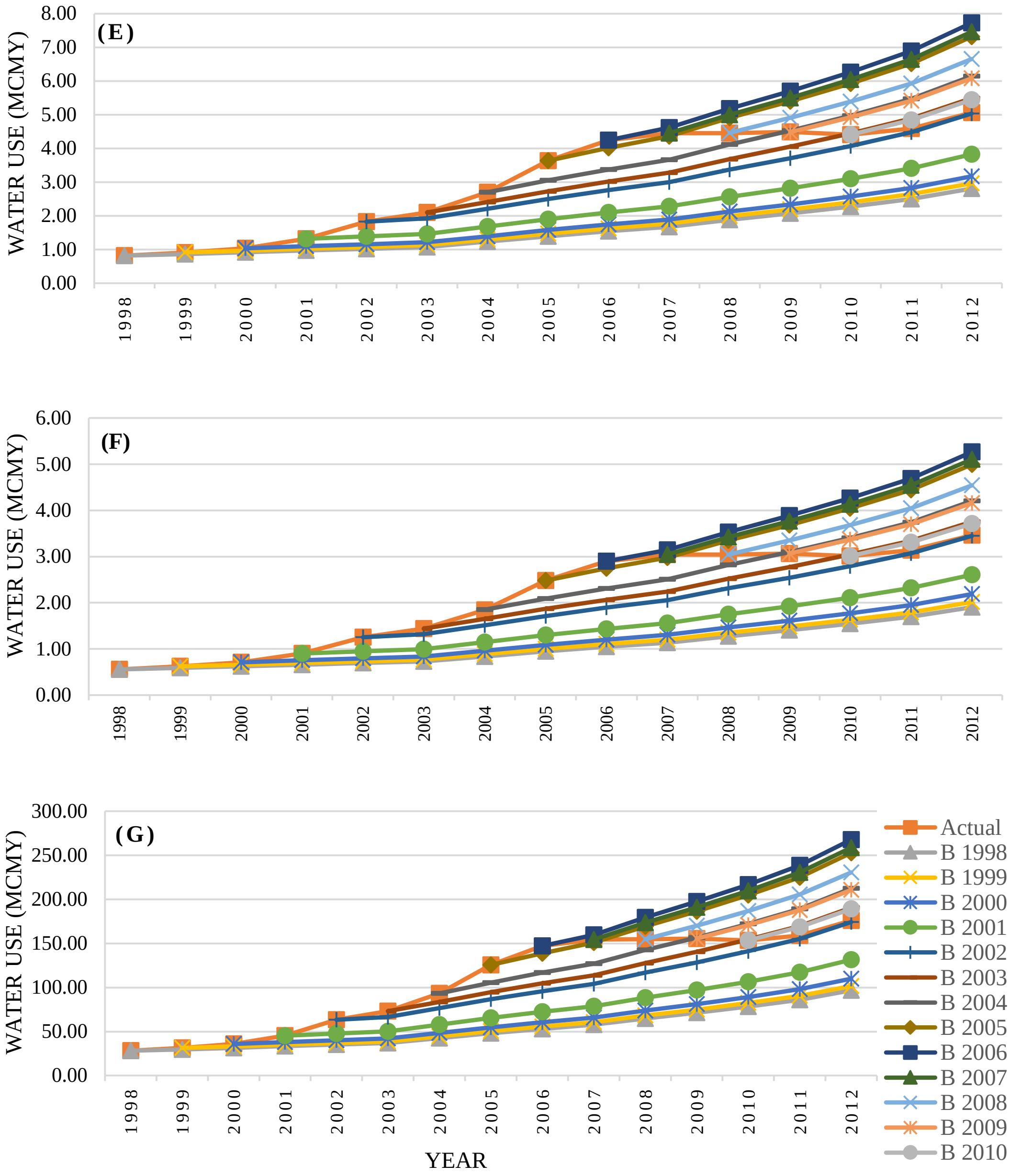


Figure 30: Actual and simulated total annual water use (database 2) using model 2 for (E) non-metered services, (F) public services, and (G) residential (Continued)

Figure 31 presents the difference between the actual and simulated water use for all calibrated base years for each sector. The simulation of base year 1998 holds the highest AARE, ARMSE and SDARE for all sectors. Except the simulation of base year 1999 holds the highest AARE for commercial and residential sectors. The SDARE of base year 2006 is close to the base year 1998 for all sectors. Figure 31 also shows that the calibration simulation with base year 2010 represents the least error compared to other calibration simulations in all sectors. So, the calibration simulation with base year 2010 is considered as the most suitable base year for this database to be used in forecasting water demand from 2013 to 2030.

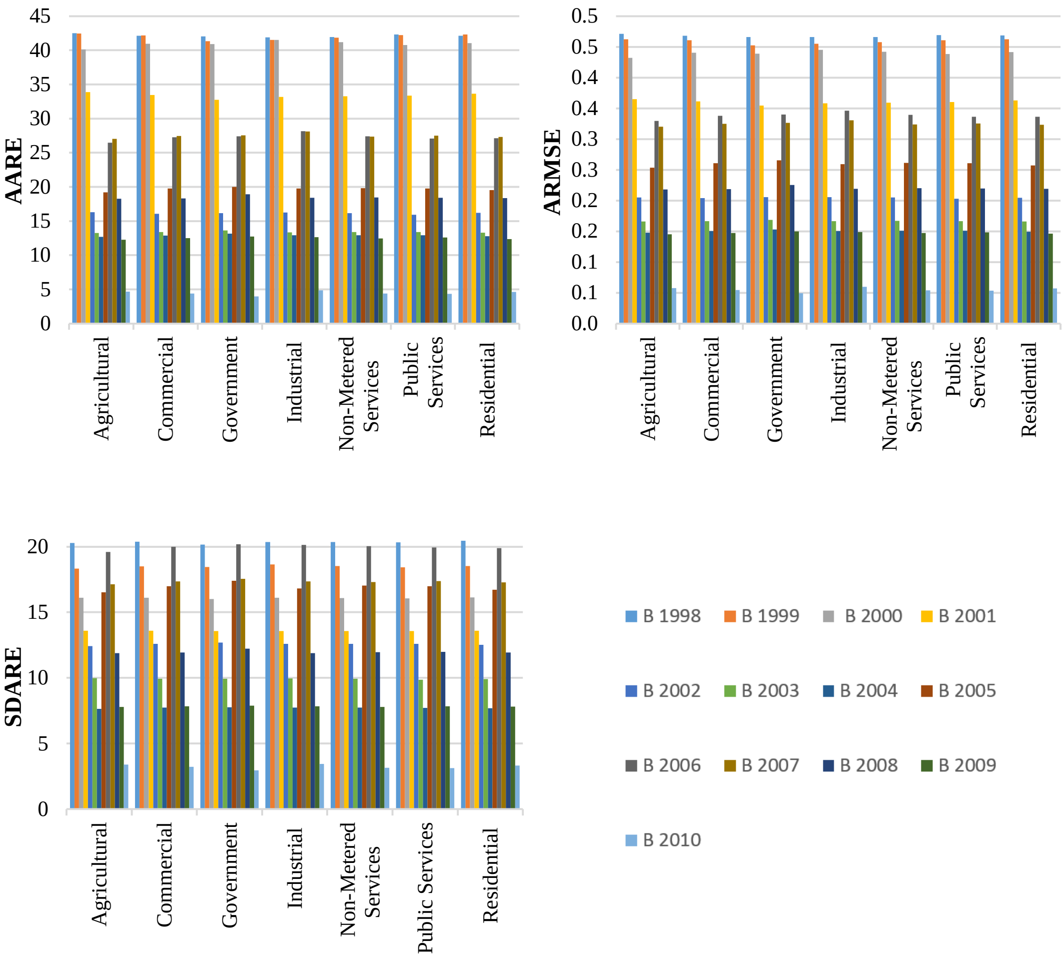


Figure 31: Error values of all calibration simulations for database 2 using model 2

5.2.3 Database 3

Total monthly water use for all sectors are simulated in IWR-MAIN with different base years. Table 23 presents the model coefficients and intercepts (β, α) obtained from SPSS and the calibration simulations for twelve months which are shown in Figure 32.

Table 23: Explanatory coefficients and intercepts (β, α) for database 3

Month	α	β
January	-1451.229328	0.010592
February	-1217.438719	0.009622
March	816.404390	0.006745
April	-729.888729	0.009128
May	1668.356303	0.005999
June	1531.240811	0.005908
July	-3811.084769	0.014918
August	-4918.296586	0.016623
September	-5300.964394	0.016890
October	-2288.803470	0.012219
November	-4542.537992	0.015372
December	-104.953726	0.008059

Figure 32 shows that the actual water consumption is generally increasing with time except for specific months in 2010 and 2011. The highest actual demand is encountered in 2012. In this year, the highest monthly water use is observed in July which is the hottest month in the year, however, the lowest water use is observed in February which has a low temperature. The explanation of this is that July is the hottest month (average temperature is 38^{o}C) of the year and February is a rainy month (average of 4.3 mm) and the average absolute temperature at this month is around 21^{o}C (AADC and SCAD, 2015).

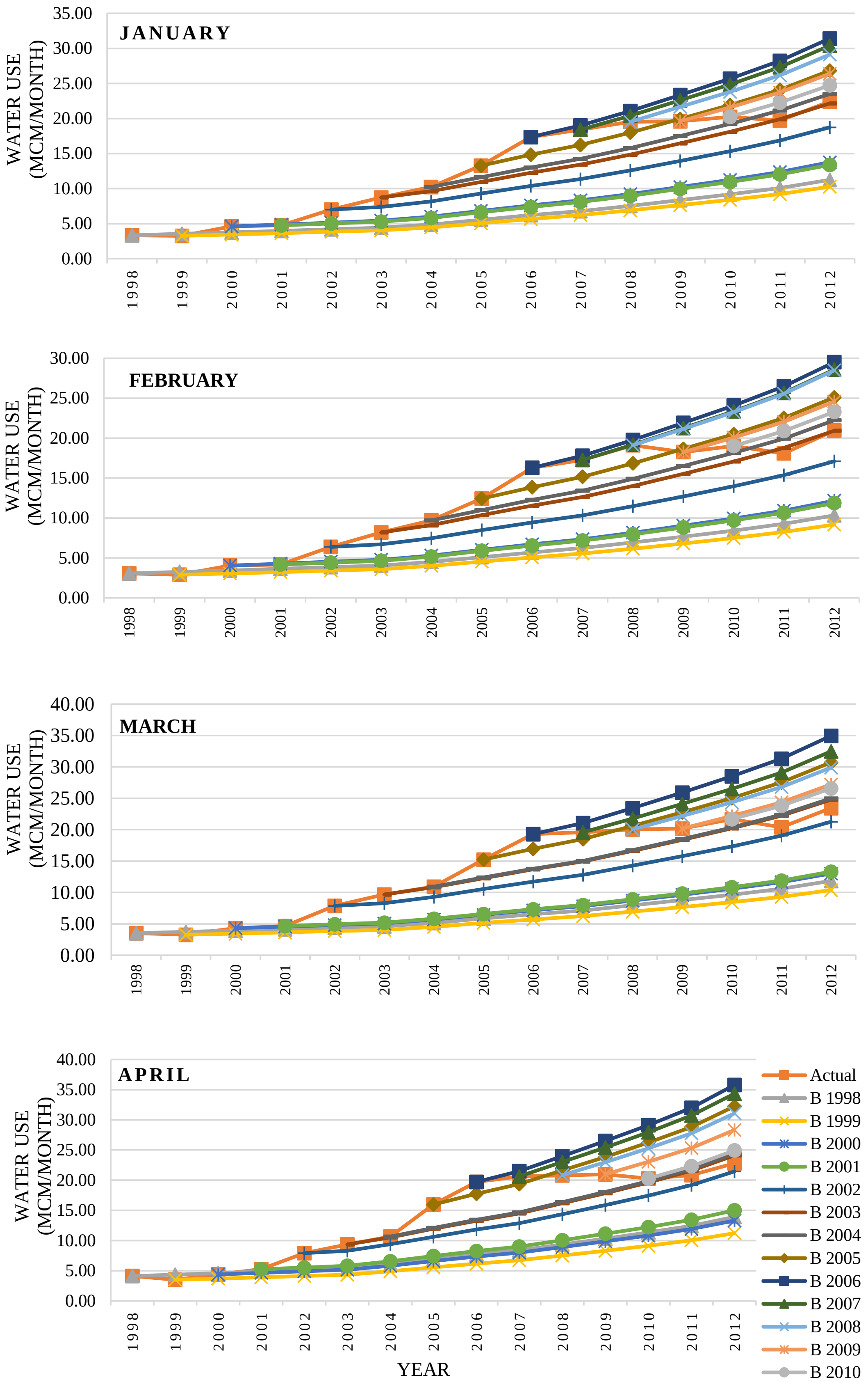


Figure 32: Actual and simulated total monthly water (database 3) using model 2

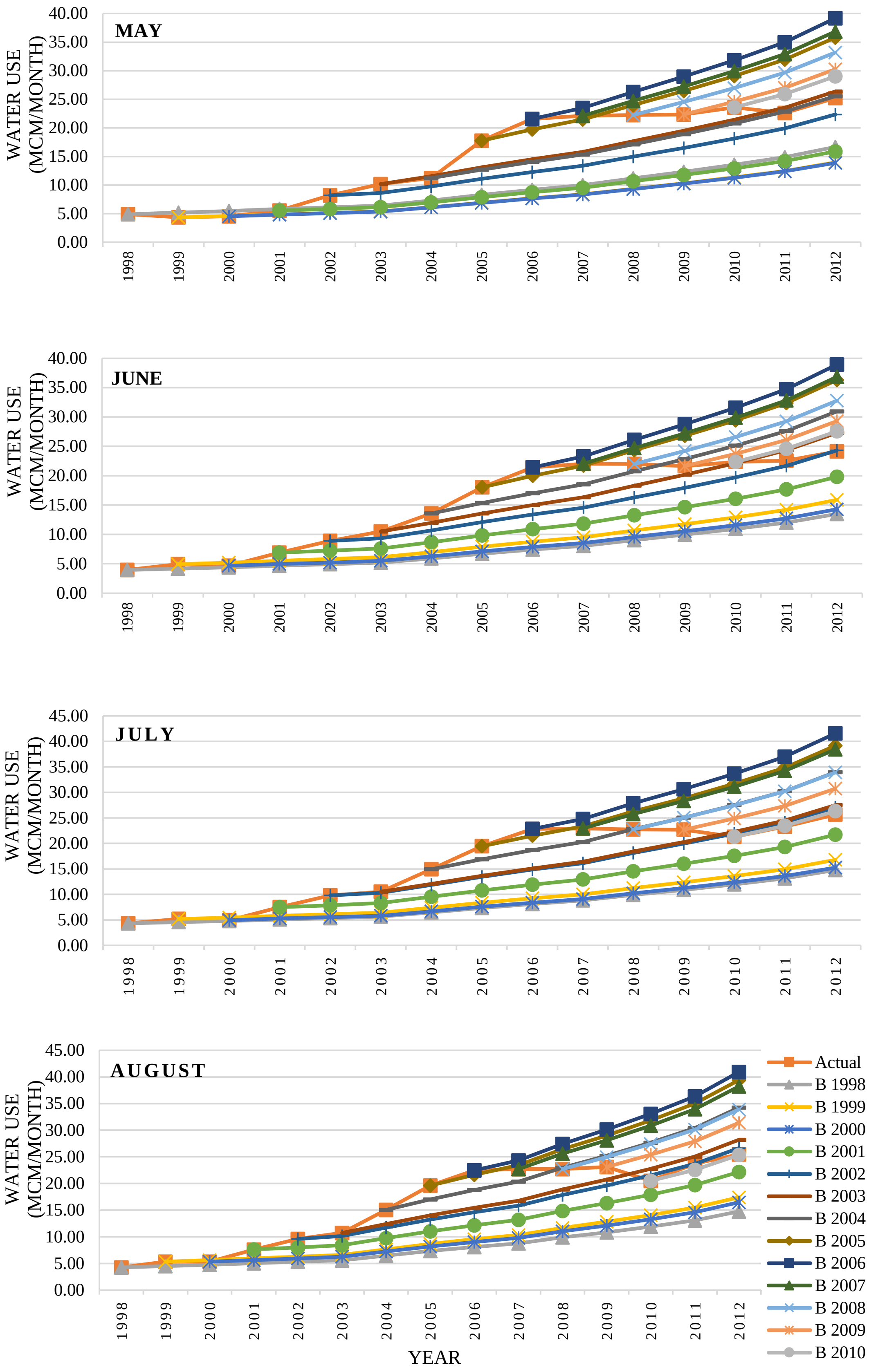


Figure 32: Actual and simulated total monthly water (database 3) using model 2 (Continued)

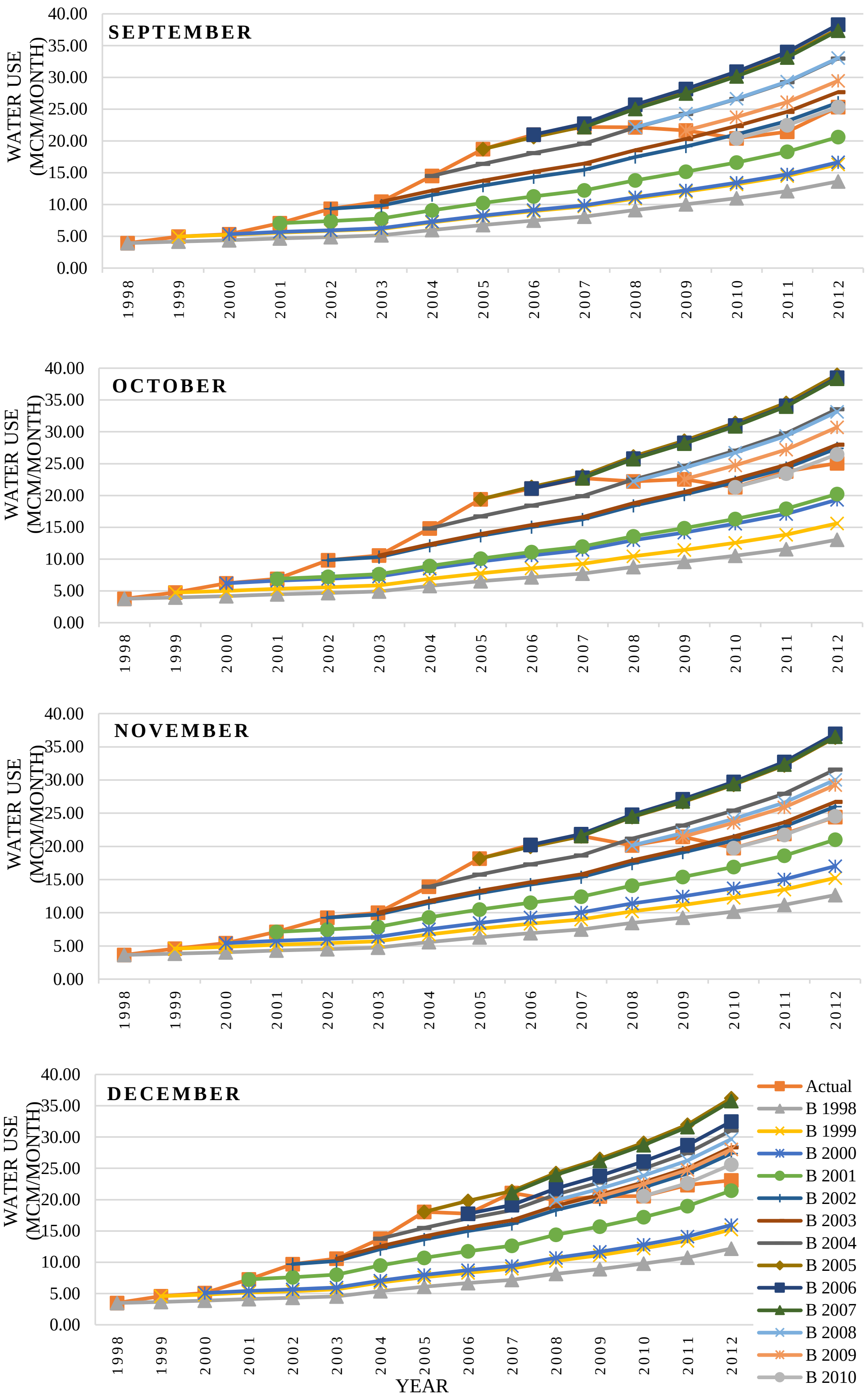


Figure 32: Actual and simulated total monthly water (database 3) using model 2 (Continued)

Figure 33 displays the values of AARE, ARMSE, and SDARE of all calibration simulations. The simulated with base year 1999 exhibits the highest AARE and ARMSE for the first four months, while simulated with base year 2000 for months of May, June , and July. The last five months of base year 1998 exhibit the highest AARE and ARMS. Figure 33 shows that the simulation of base year 1998 holds the highest SDARE for the first three month of the years. May of 1999 shows the highest SDARE; whereas, October and December of base year 2005 hold the highest SDARE. The simulated with base year 2006 hold the highest SDARE for the rest six months. Following the same criteria used in previous databases, Table 24 shows the best base year for each month that will be considered for the forecasting scenarios.

Table 24: Best base years for database 3 using model 2

Month	Base Year	Month	Base Year
January	2004	July	2010
February	2004	August	2010
March	2009	September	2010
April	2010	October	2010
May	2009	November	2010
June	2009	December	2010

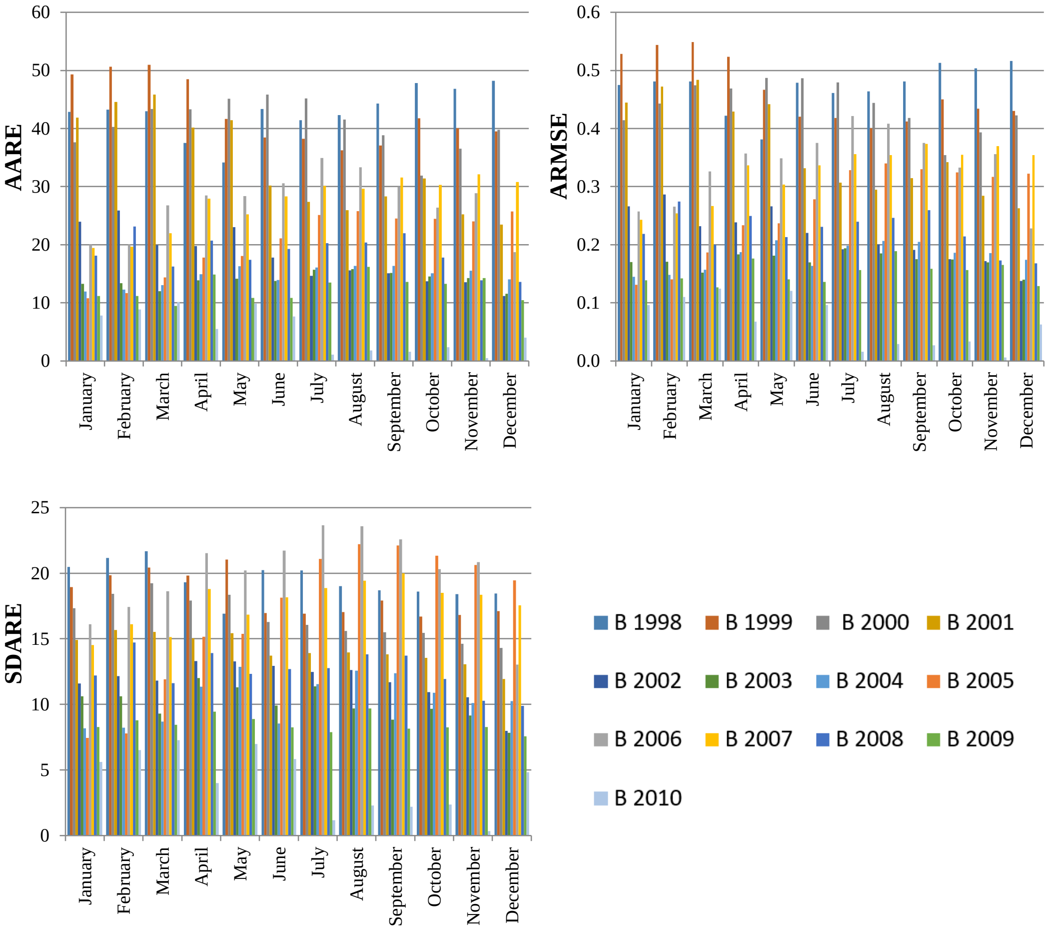


Figure 33: Error values of all calibration simulations for database 3 using model 2

5.2.4 Database 4

Seven sectors were calibrated monthly by various base years. To simplify the results, each sector is discussed separately below. Table 25 shows the model coefficients and intercepts (β, α) obtained from SPSS program for each sector.

Table 25: Explanatory coefficients and intercepts (β, α) for database 4

		Agricultural	Commercial	Government	Non-metered Services	Industrial	Public Services	Residual
January	α	-234.46	-65.49	-262.65	-21.97	-6.54	-16.60	-843.53
	β	0.00171	0.00048	0.00192	0.00016	0.00005	0.00012	0.00616
February	α	-109.31	-57.13	-310.31	-20.26	0.06	-12.47	-707.09
	β	0.00086	0.00045	0.00245	0.00016	0.00001	0.00010	0.00559
March	α	71.38	49.47	42.69	14.40	3.07	10.50	624.90
	β	0.00059	0.00041	0.00035	0.00012	0.00003	0.00009	0.00516
April	α	-53.92	-45.97	-136.96	-11.61	-1.77	-11.06	-468.60
	β	0.00067	0.00058	0.00171	0.00015	0.00002	0.00014	0.00586
May	α	184.99	85.88	374.91	35.26	5.86	16.26	964.36
	β	0.00067	0.00031	0.00135	0.00013	0.00003	0.00006	0.00347
June	α	161.79	83.02	311.76	24.86	8.17	16.69	924.96
	β	0.00062	0.00032	0.00120	0.00010	0.00003	0.00006	0.00357
July	α	-298.71	-198.18	-736.97	-67.02	-13.97	-42.96	-2453.27
	β	0.00117	0.00078	0.00289	0.00026	0.00006	0.00017	0.00960
August	α	-390.01	-292.71	-1723.40	-110.59	-17.31	-58.46	-2325.83
	β	0.00132	0.00099	0.00583	0.00037	0.00006	0.00020	0.00786
September	α	-409.55	-215.16	-1053.62	-87.15	-15.40	-64.24	-3455.83
	β	0.00131	0.00069	0.00336	0.00028	0.00005	0.00021	0.01101
October	α	-411.66	-133.20	-537.77	-31.10	-5.82	-30.16	-1139.09
	β	0.00220	0.00071	0.00287	0.00017	0.00003	0.00016	0.00608
November	α	-401.99	-261.71	-508.35	-90.80	-12.41	-60.57	-3206.69
	β	0.00136	0.00089	0.00172	0.00031	0.00004	0.00021	0.01085
December	α	-10.34	-5.64	-21.01	-1.85	-0.34	-1.27	-64.50
	β	0.00079	0.00043	0.00161	0.00014	0.00003	0.00010	0.00495

5.2.4.1 Agricultural Sector

Figure 34 shows a plot of the actual and simulated water use for agricultural sector for twelve months with different base years. It shows that the highest actual water use is encountered in 2012. In this year, the highest monthly water use is observed in October (average temperature is 31^{o}C) (AADC, 2015). This is because most families returning from summer holiday in October.

Figure 35 demonstrates the AARE, ARMSE, and SDARE for the 12 months of the year for all simulated base years. It shows that the simulation of base year 1999 shows the highest AARE and ARMSE for first four month of the year. The base year 2000 shows the highest AARE and ARMSE for months of May, June, and July; however, the last five months of the year have the highest AARE and ARMSE with the simulation of base year 1998. The first three months of base year 1998 shows the highest SDARE, while the May of base year 1999 has the highest SDARE. October and November of base year 2005 have the highest SDARE and the other months with base year 2006. Based on the same criteria for selected the most suitable base year, April and last six months of the year with base year of 2010 show the least AARE and ARMSE. However, the minimum SDARE with longer calibration period is obtained for March, May, and June with base year 2009; whereas base year 2004 for months of January and February.

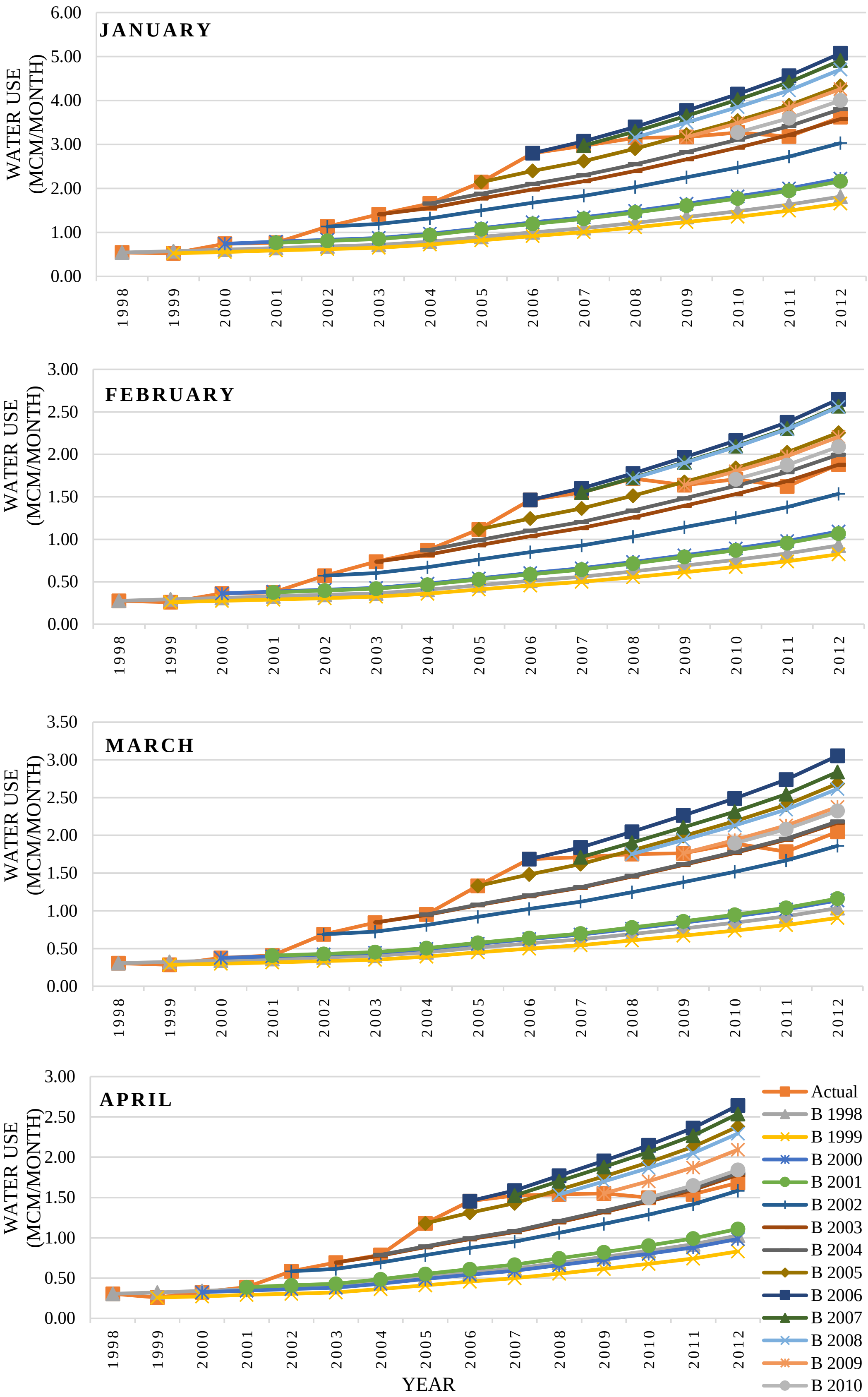


Figure 34: Actual and simulated monthly water use for agricultural sector using model 2

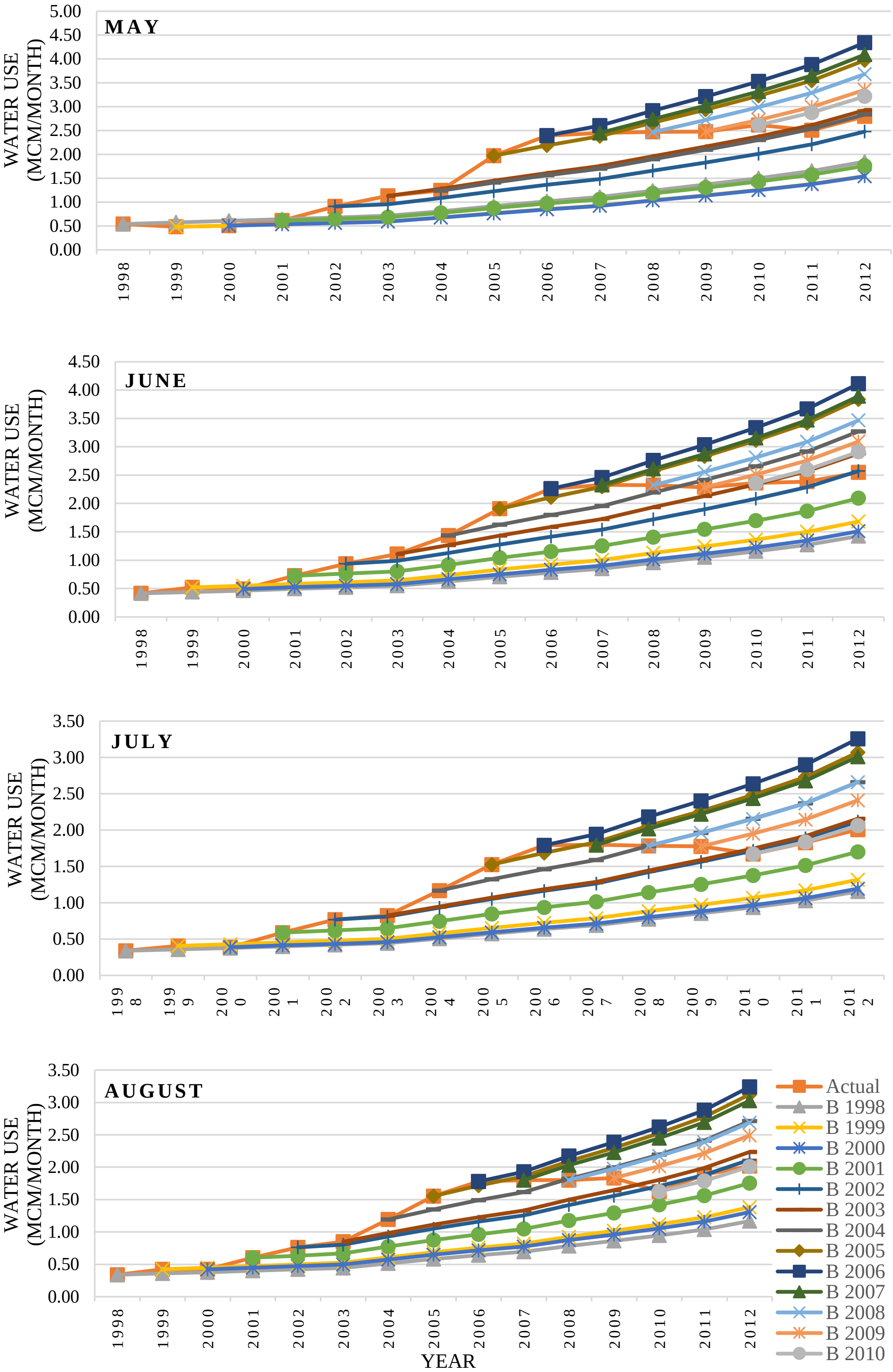


Figure 34: Actual and simulated monthly water use for agricultural sector using model 2

(Continued)

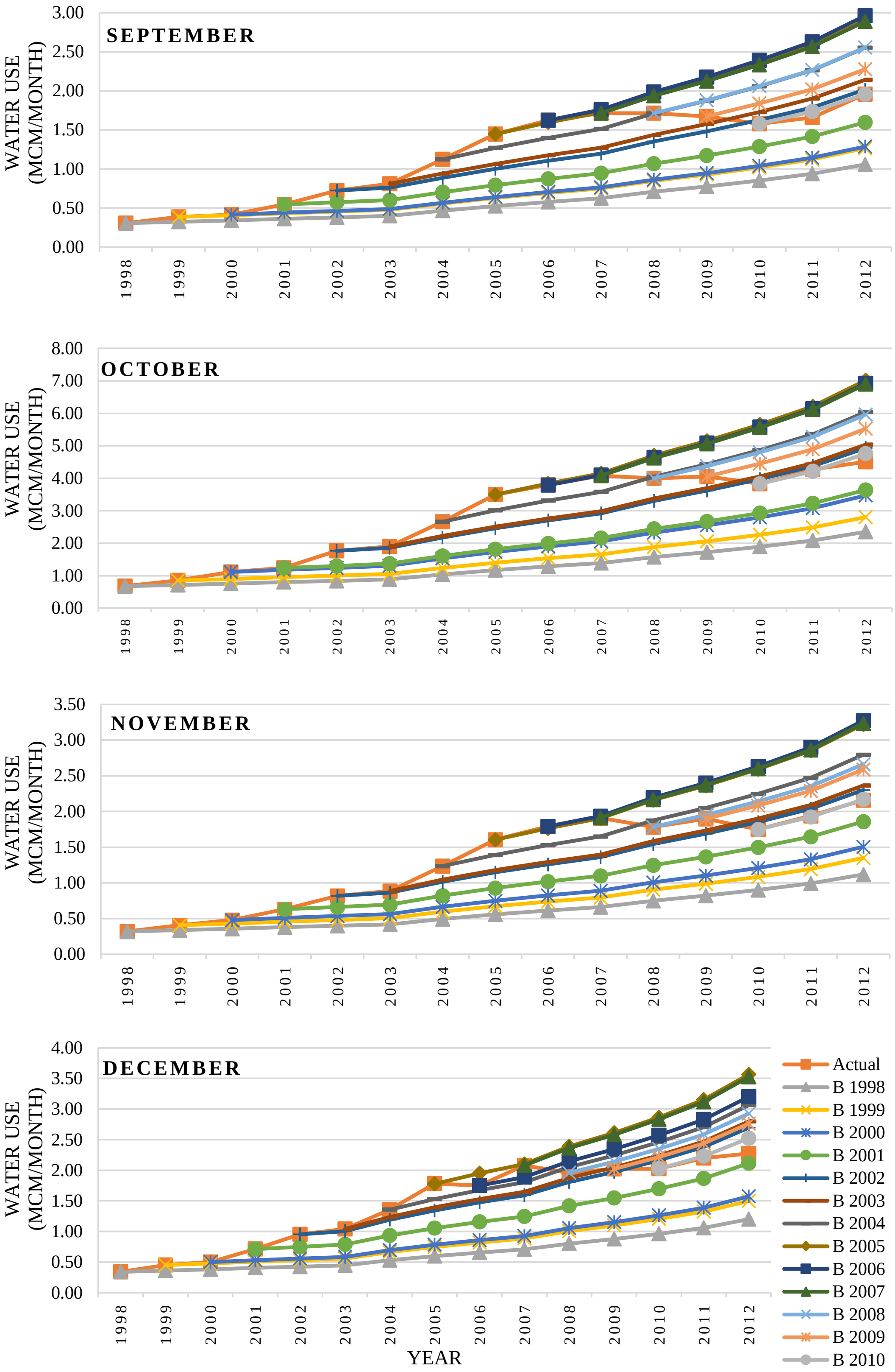


Figure 34: Actual and simulated monthly water use for agricultural sector using model 2

(Continued)

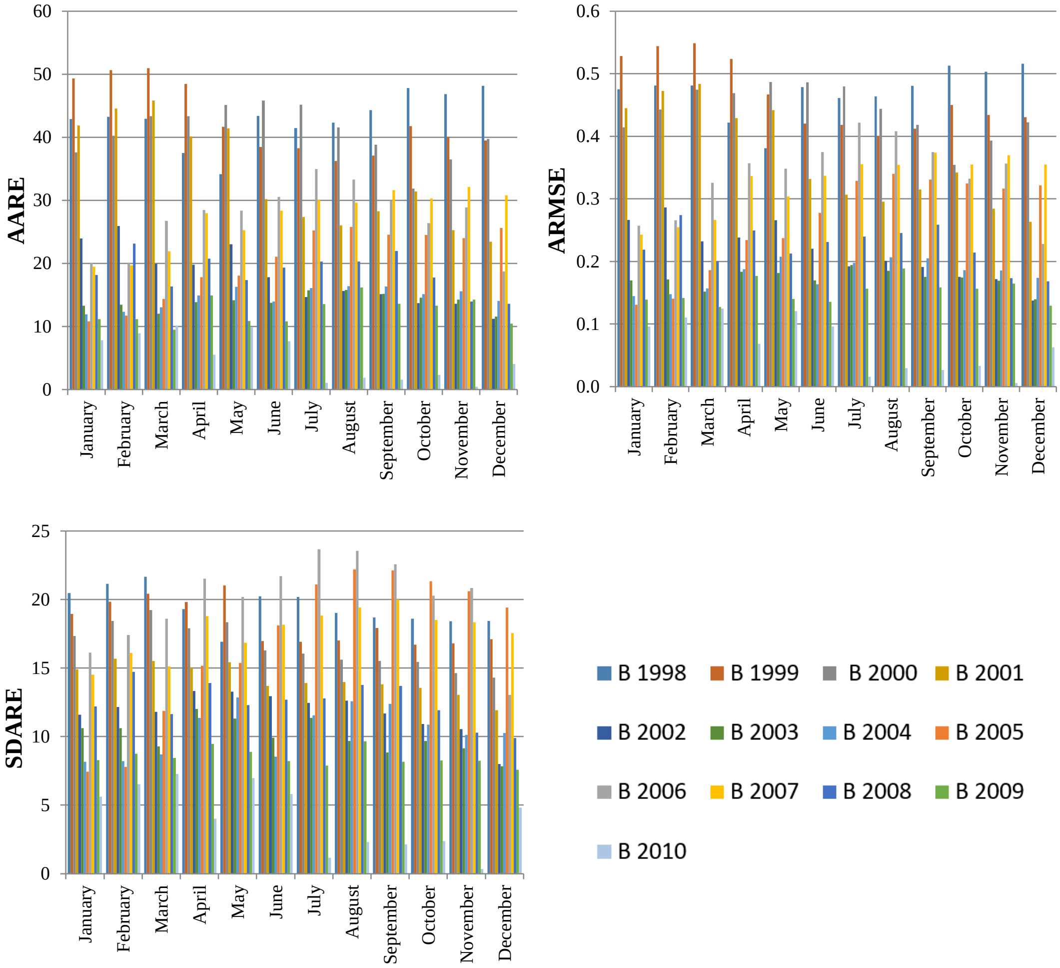


Figure 35: Error values of all calibration simulations for agricultural sector (database 4) using model 2

5.2.4.2 Residential Sector

Figure 36 illustrates the actual and simulated water use for residential sector with different base years. It shows that the highest actual consumption is encountered in 2012. In this year, the highest monthly consumption is observed in March which has an average temperature of 24^{o}C and average precipitation of around 0.5 mm, and the lowest monthly consumption is observed in February which has an average temperature of 21^{o}C and average precipitation of around 4.3 mm (AADC and SCAD, 2015).

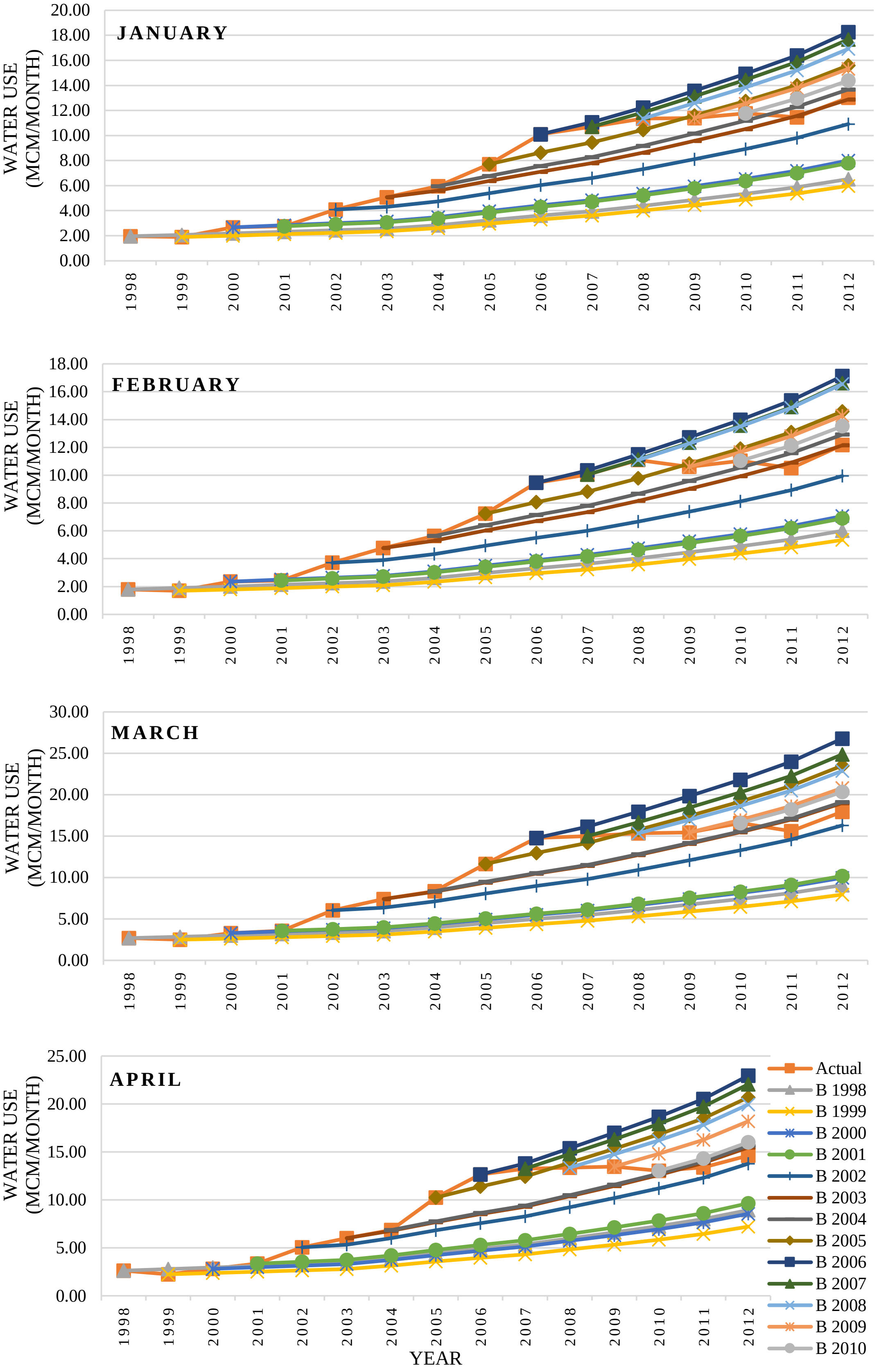


Figure 36: Actual and simulated monthly water use for residential sector using model 2

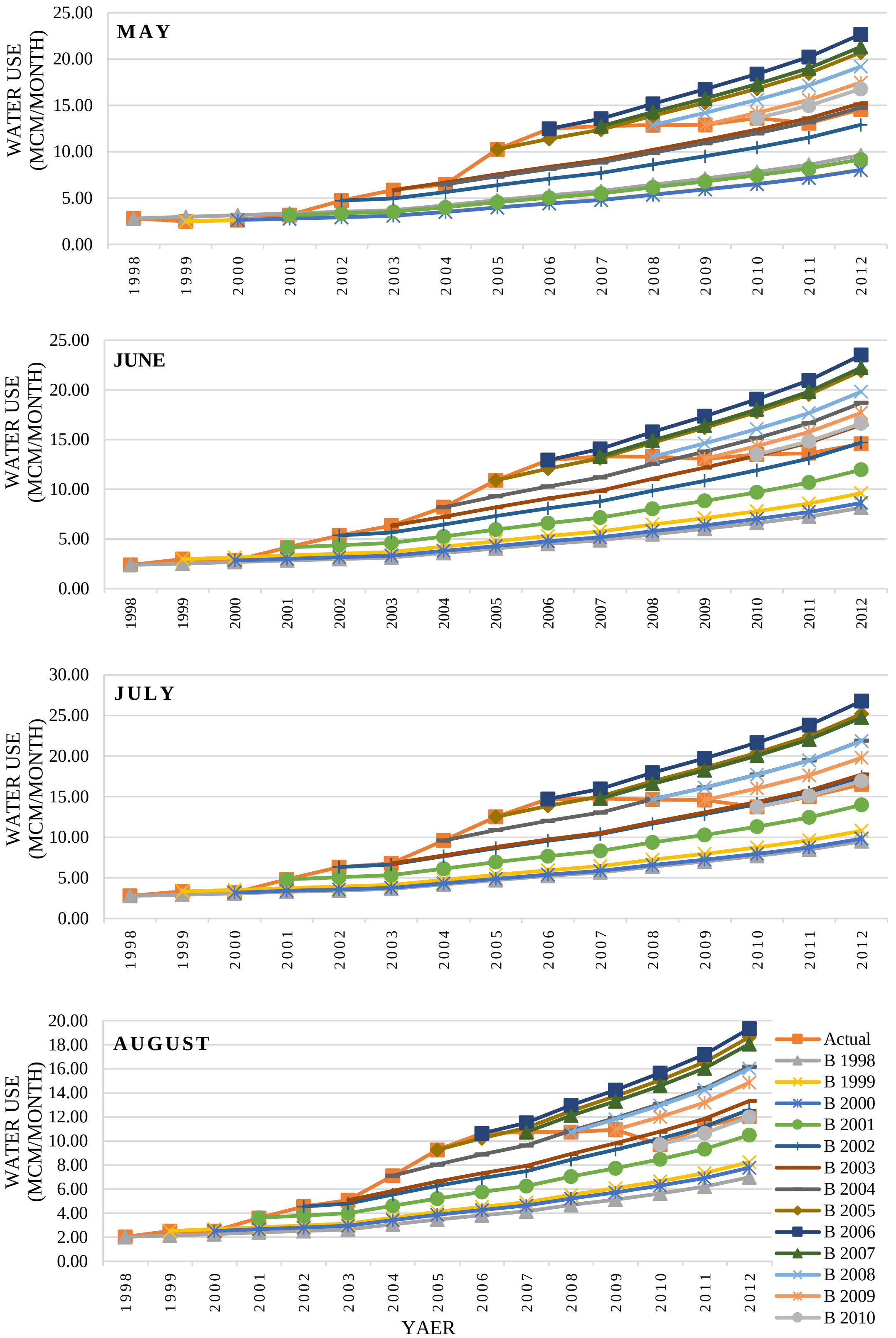


Figure 36: Actual and simulated monthly water use for residential sector using model 2

(Continued)

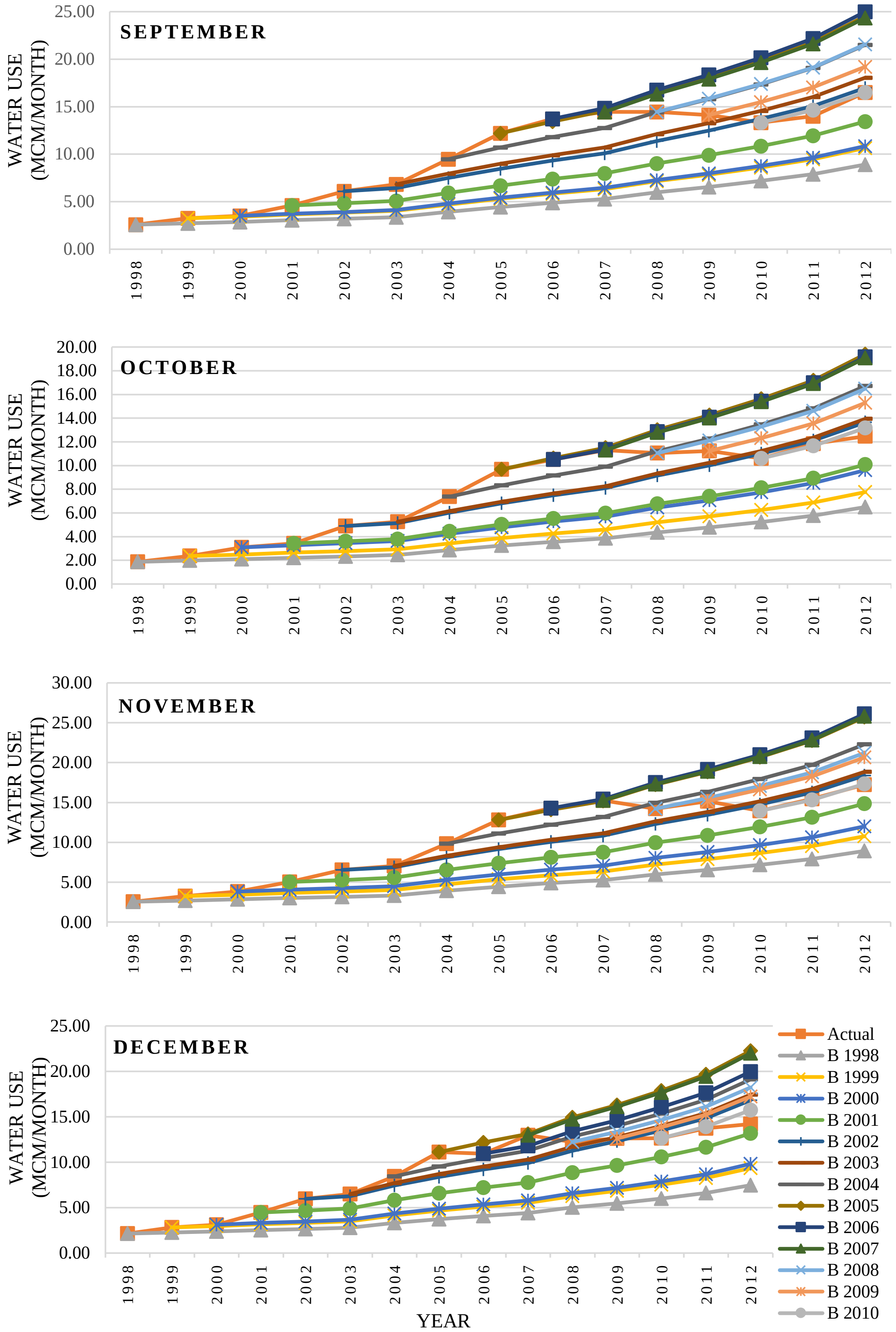


Figure 36: Actual and simulated monthly water use for residential sector using model 2

(Continued)

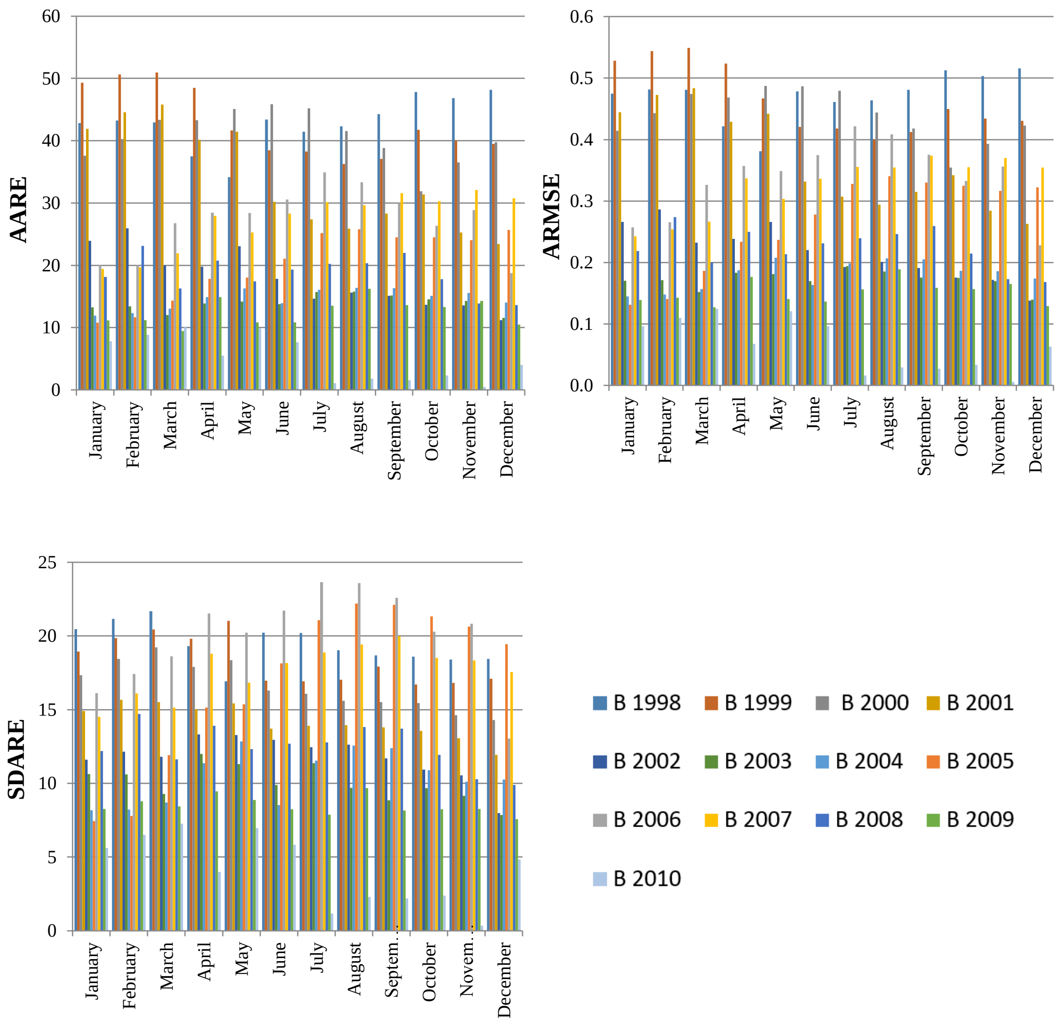


Figure 37: Error values of all calibration simulations for residential sector (database 4) using model 2

Figure 37 represents the calculated AARE, ARMSE, and SDARE for all calibration simulations for the twelve months of the year. Also, Figure 37 is used to select the best base year to forecast water demand for a specific month. The results concluded that the base year 2010 is selected for April and for last six months of the year. The base year 2009 is selected for March, May, and June, whereas the base year 2004 is selected for months of January and February.

5.2.4.3 Non-metered Services Sector

Figure 38 shows the calibration simulations for non-metered services with different base years. It shows that the highest and lowest actual consumption are observed in year 2012 in months of August (average temperature is 37ºC) and February (has a low average temperature of 21ºC), respectively (AADC, 2015).

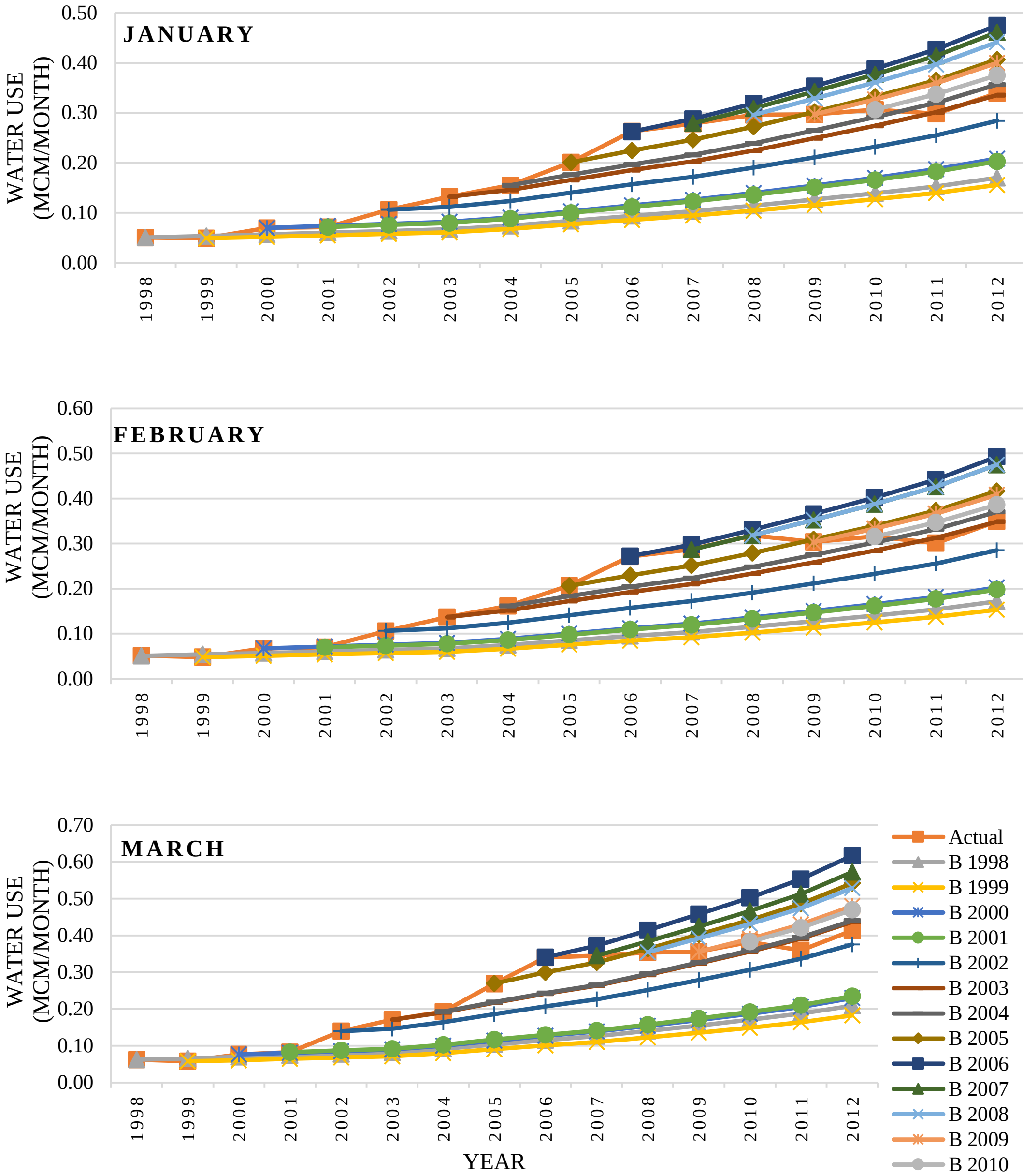


Figure 38: Actual and simulated monthly water use for non-metered services sector using model 2

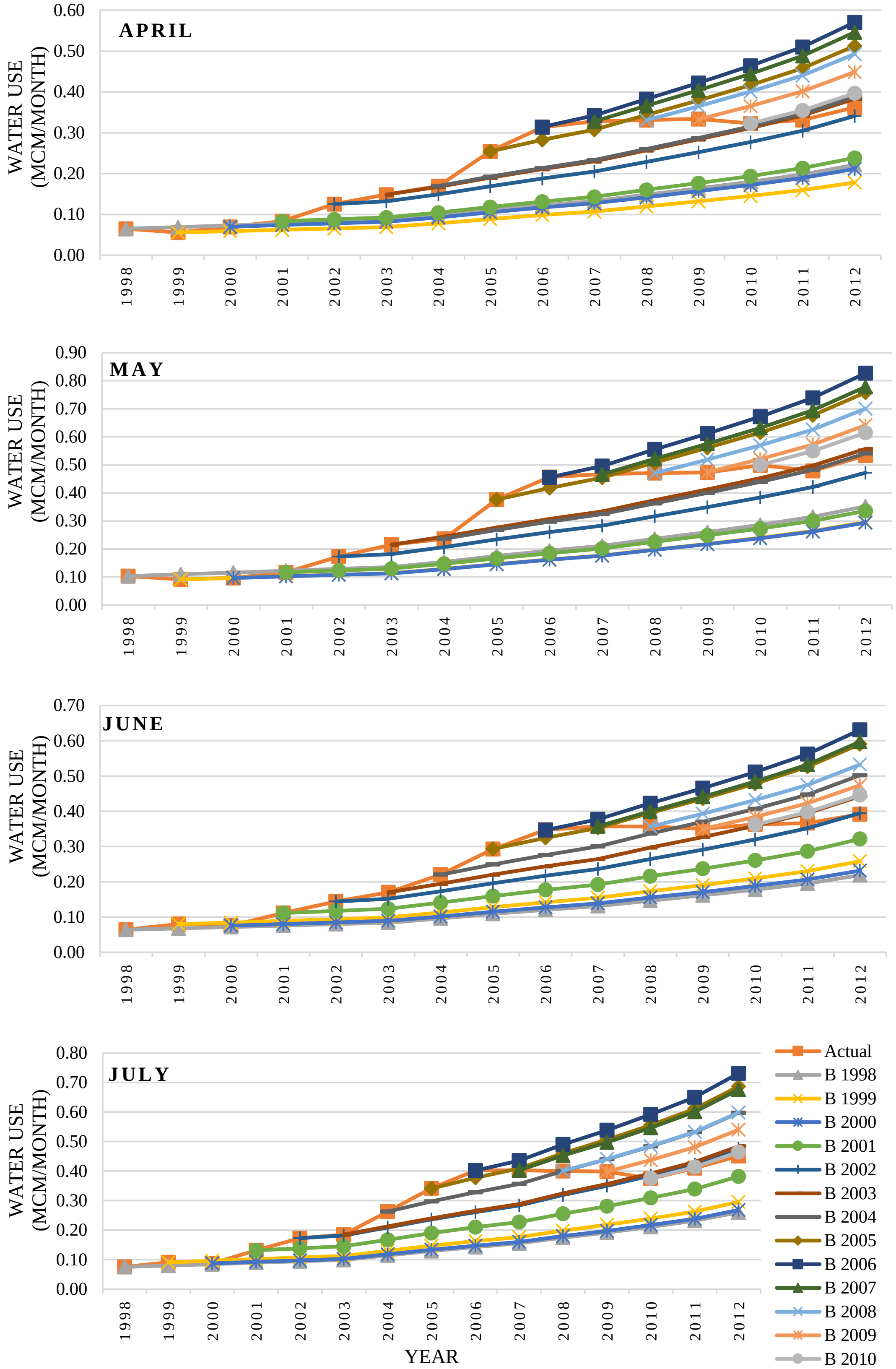


Figure 38: Actual and simulated monthly water use for non-metered services sector using model 2 (Continued)

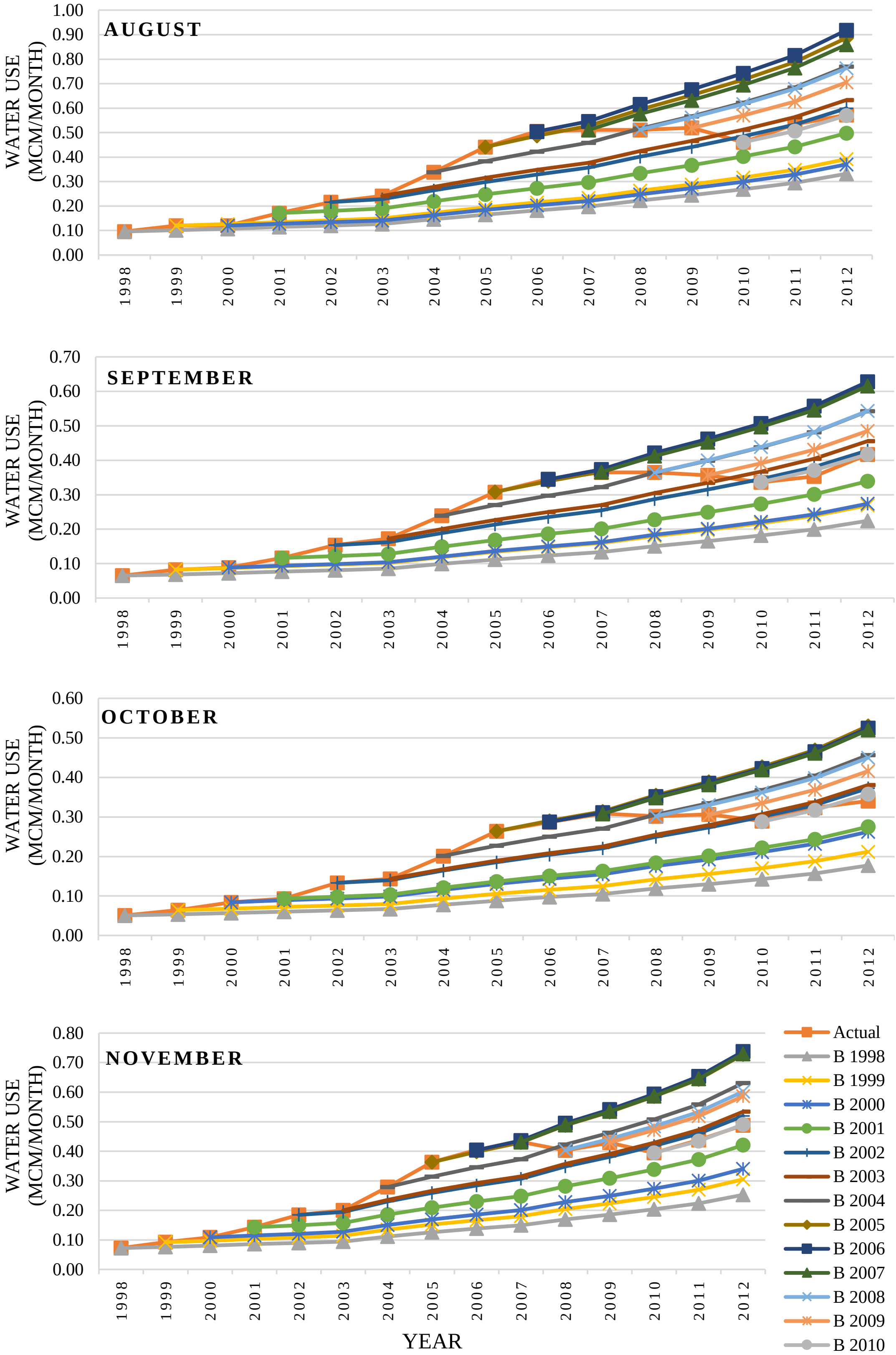


Figure 38: Actual and simulated monthly water use for non-metered services sector using model 2 (Continued)

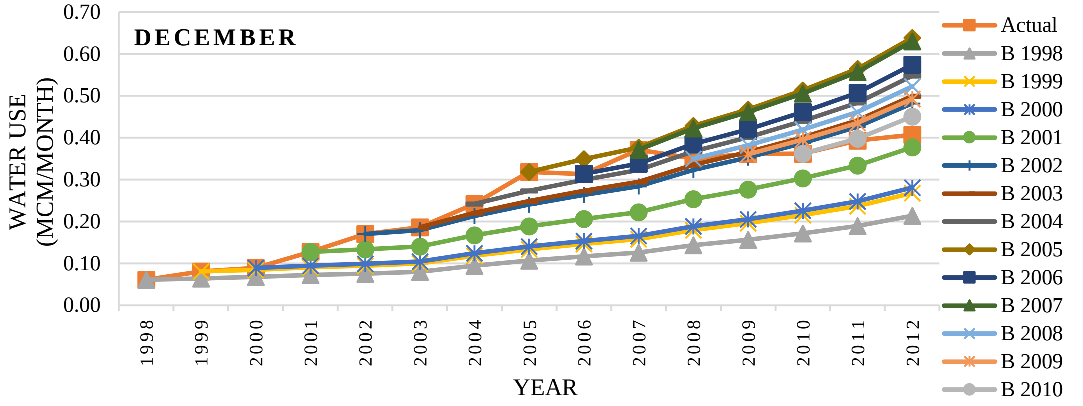


Figure 38: Actual and simulated monthly water use for non-metered services sector using model 2 (Continued)

Figure 39 represents the calculated AARE, ARMSE, and SDARE for all calibration simulations. The results concluded that base year 2010 is selected for April and for last six months of the year. The base year 2009 is selected for March, May, and June, while the base year 2004 is selected for months of January and February.

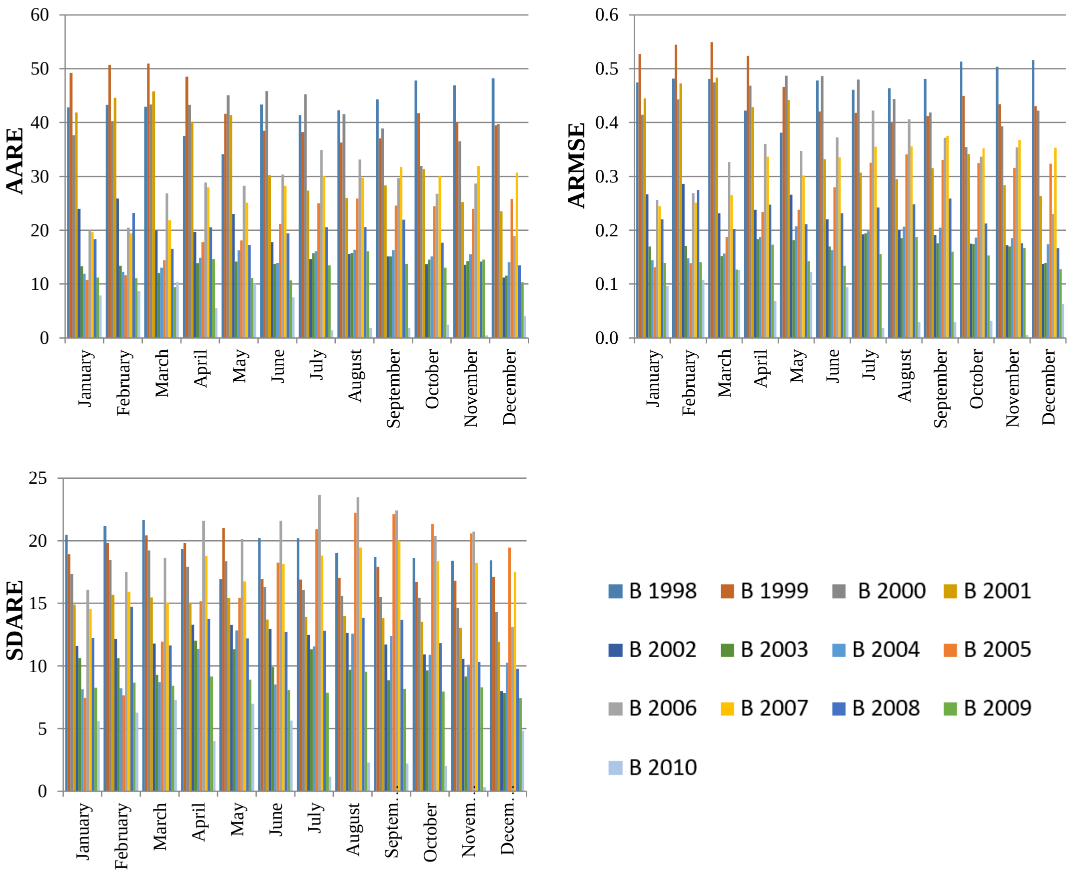


Figure 39: Error values of all calibration simulations for non-metered services sector (database 4) using model 2

5.2.4.4 Commercial Sector

Figure 40 shows the actual and calibrated monthly water use for commercial sector with different base years. The highest actual consumption is observed in August (average temperature is 37°C) in year 2012 and the lowest actual consumption is observed in February (average temperature is 21°C) in the same year (AADC, 2015). Figure 41 presents the calculated AARE, ARMSE, and SDARE for all calibration simulations. It shows that the base year 2010 is selected for April and for last six months of the year. Year 2009 would be the best base year for March, May, and June. While, year 2004 would be the best for January and February.

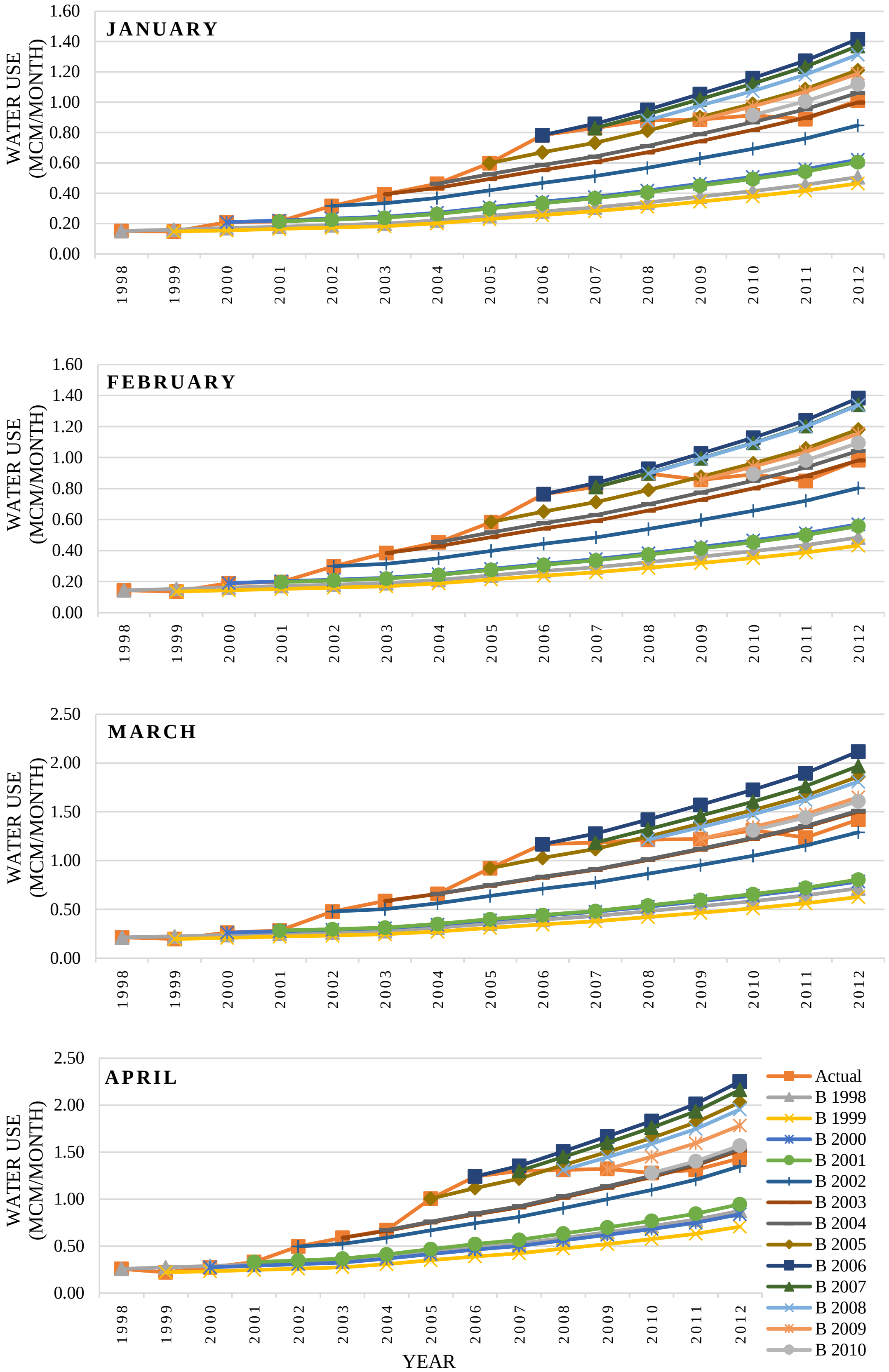


Figure 40: Actual and simulated monthly water use for commercial sector using model 2

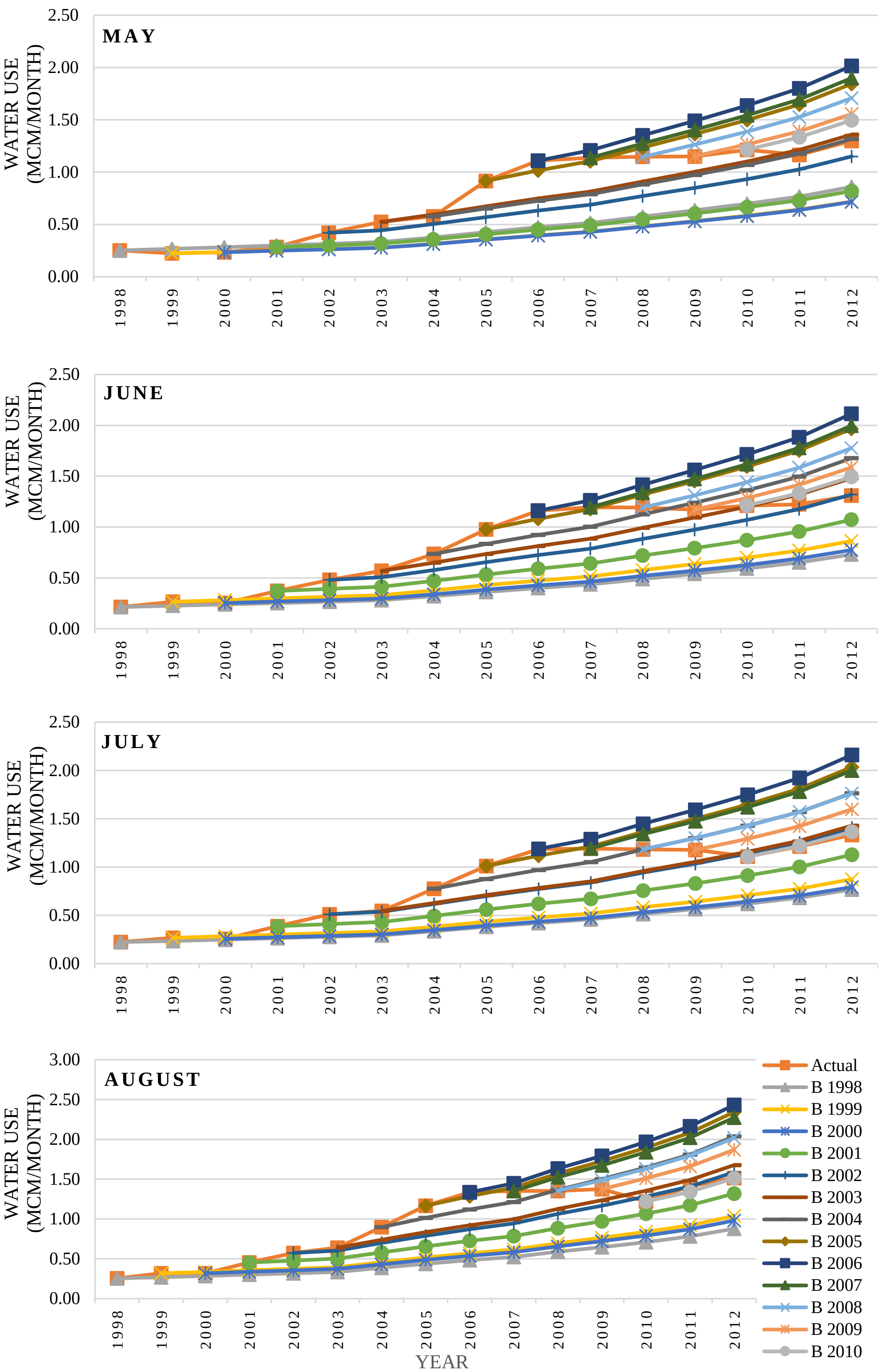


Figure 40: Actual and simulated monthly water use for commercial sector using model 2

(Continued)

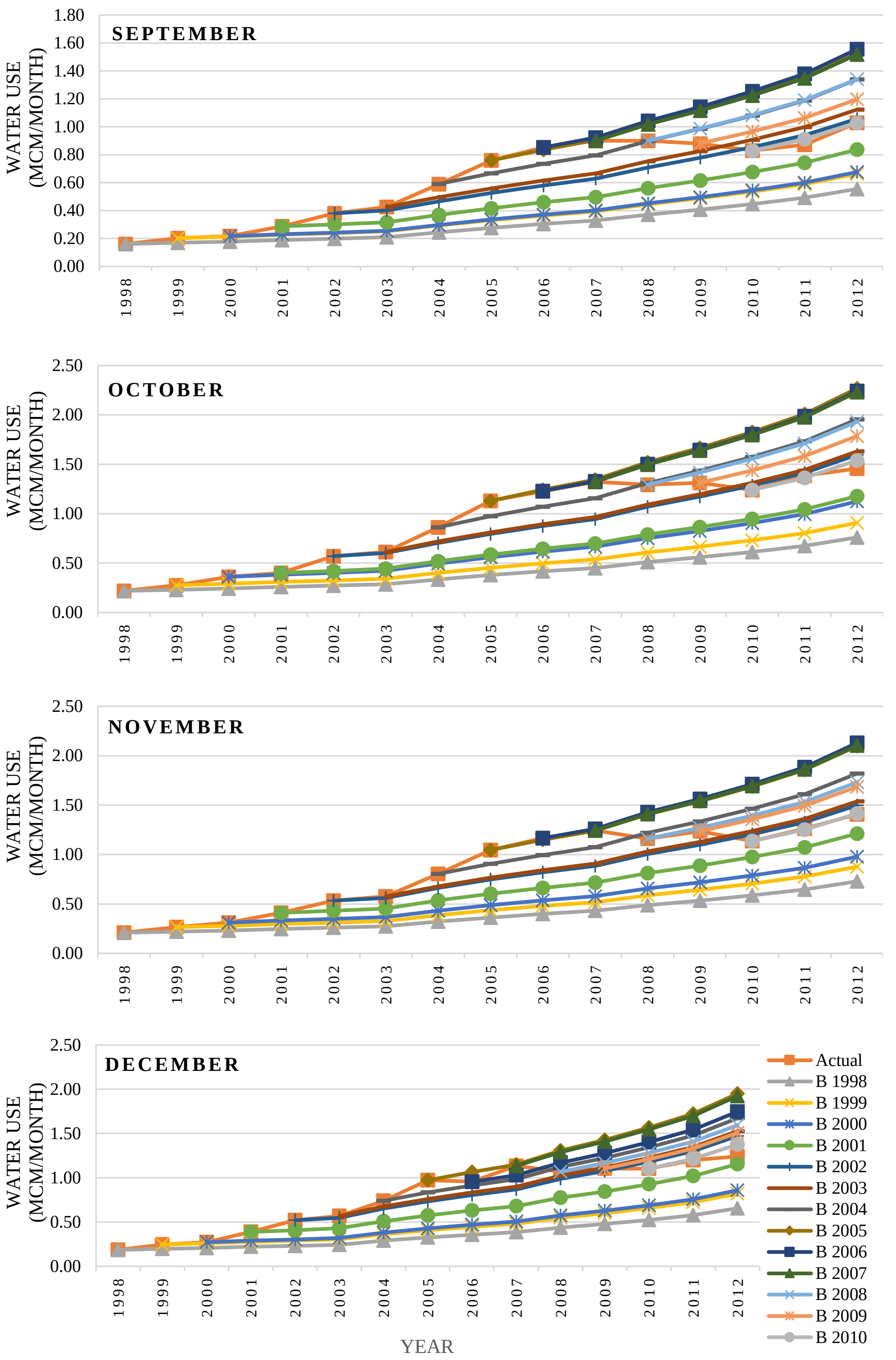


Figure 40: Actual and simulated monthly water use for commercial sector using model 2

(Continued)

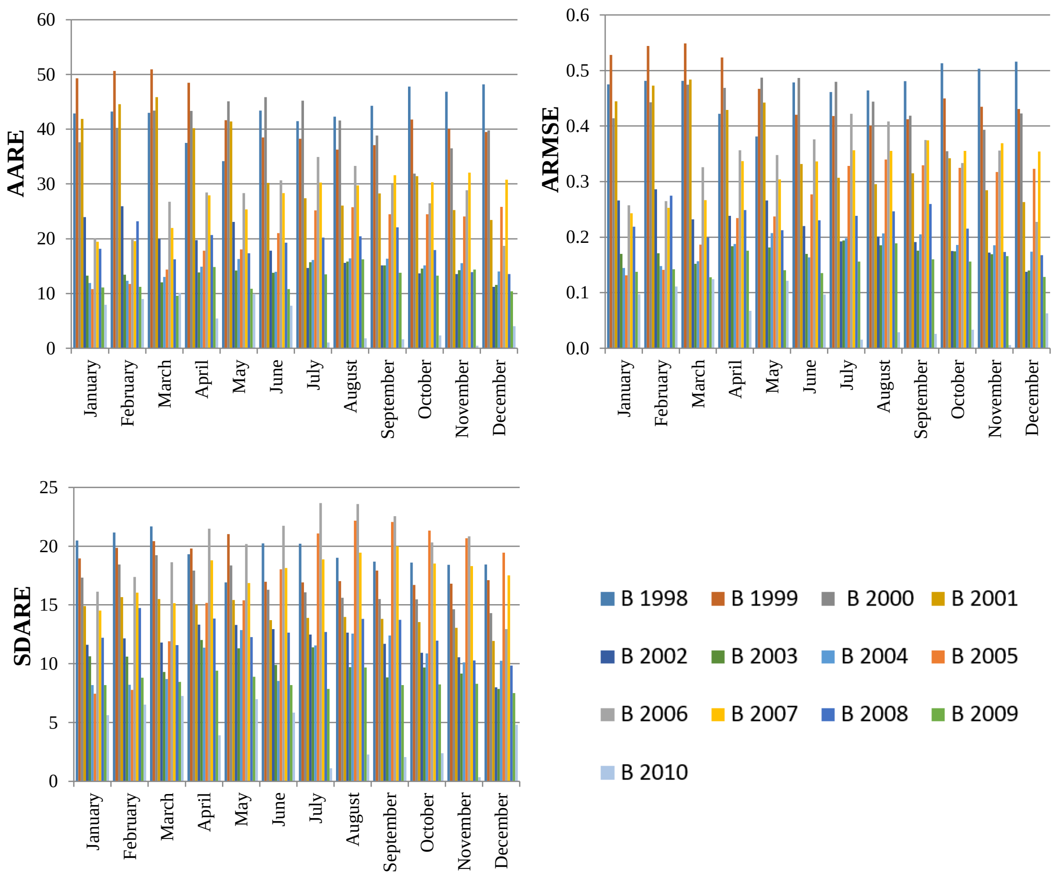


Figure 41: Error values of all calibration simulations for commercial sector (database 4) using model 2

5.2.4.5 Government Sector

Figure 42 displays the actual and simulated water use for government sector. In year 2012, the actual consumption is observed in August (average temperature is 37^{o}C) and the lowest actual consumption is observed in March (average temperature is 24^{o}C) (AADC, 2015). Figure 43 shows the values of AARE, ARMSE, and SDARE for all calibration simulations. Year 2010 would be the best base year to forecast future demand in April and last six months of the year. While, year 2009 would be the best base year for March, May, and June. Years 2004 would be the best for January and February.

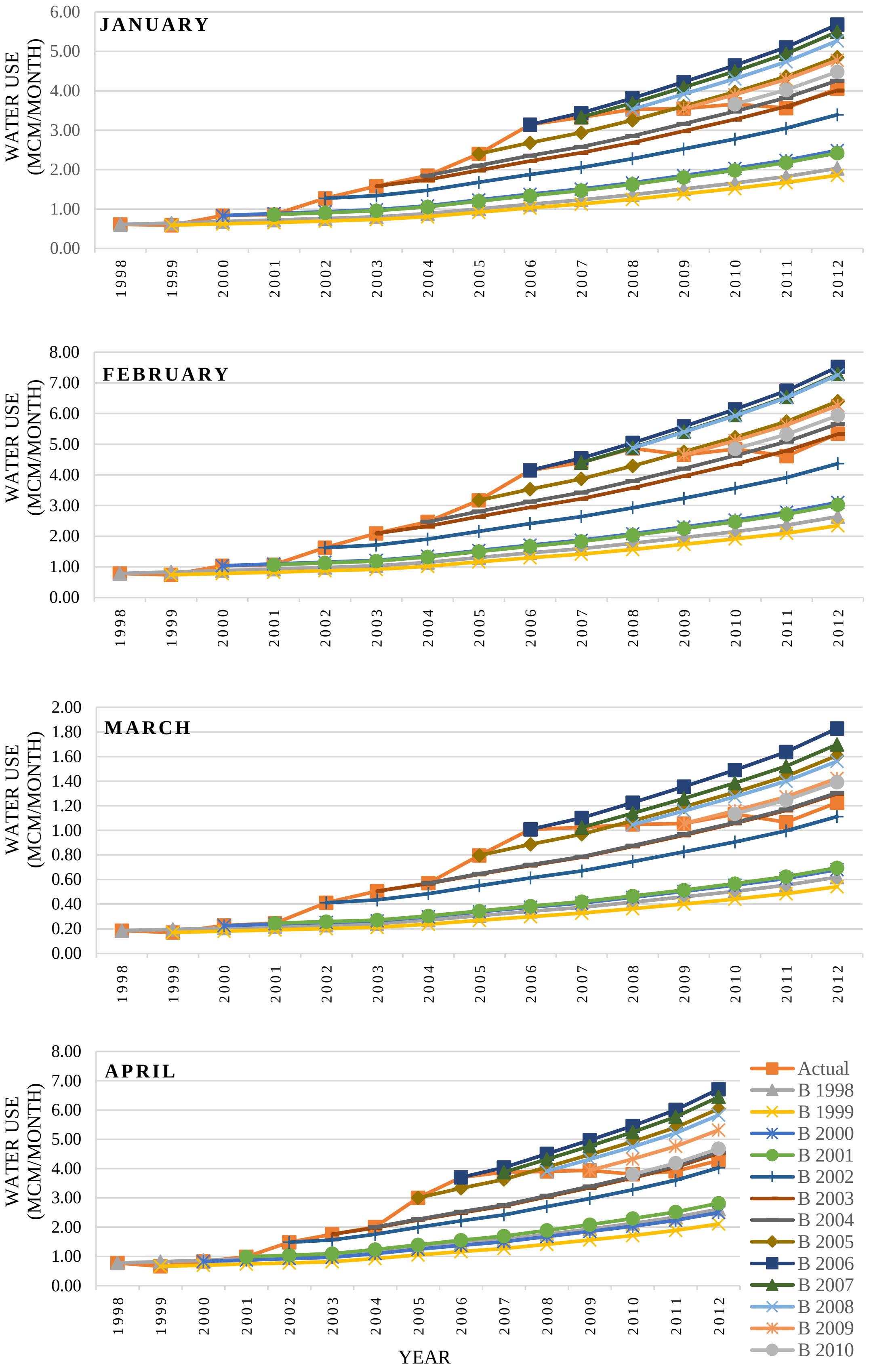


Figure 42: Actual and simulated monthly water use for government sector using model 2

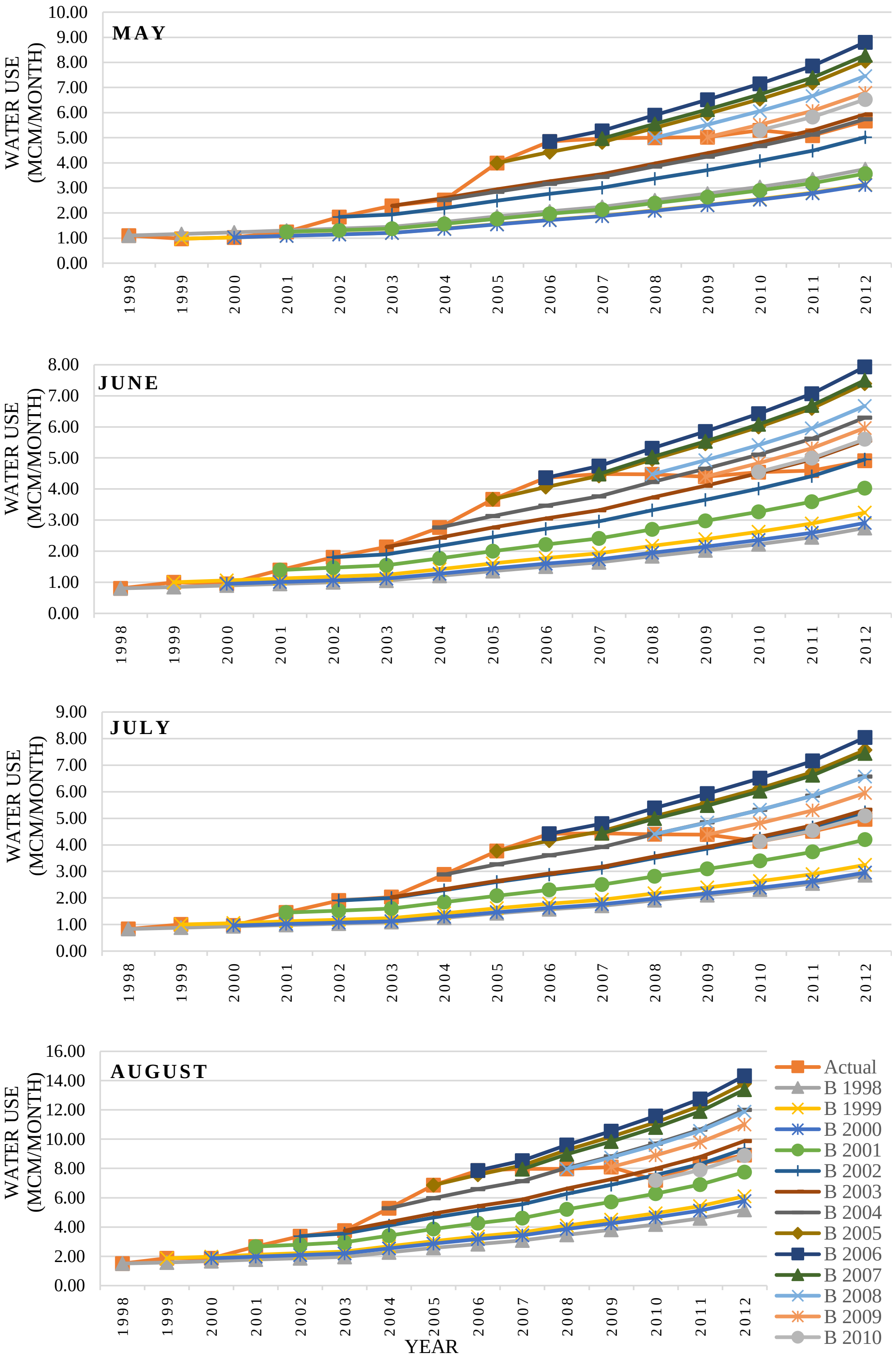


Figure 42: Actual and simulated monthly water use for government sector using model 2

(Continued)

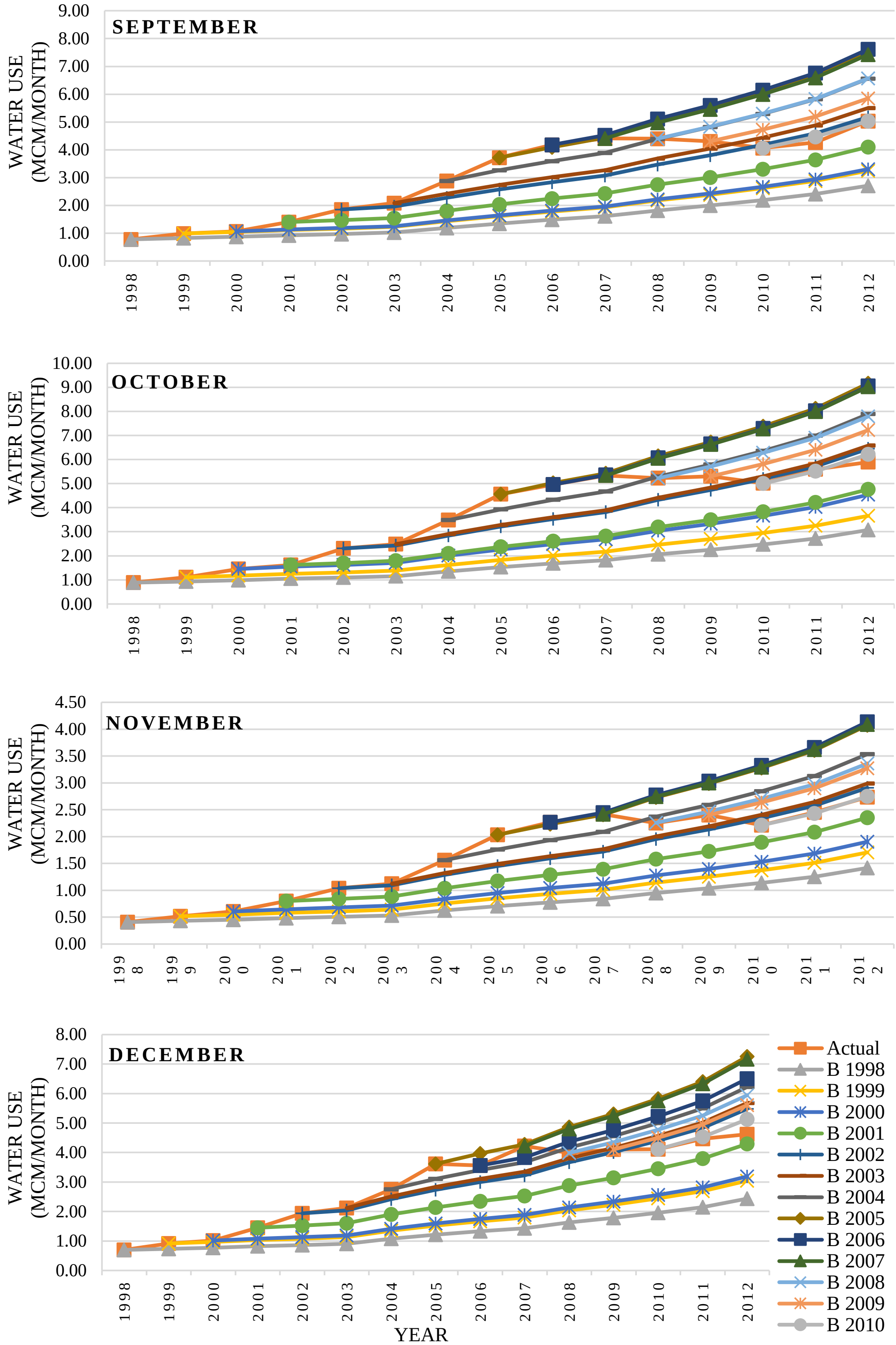


Figure 42: Actual and simulated monthly water use for government sector using model 2

(Continued)

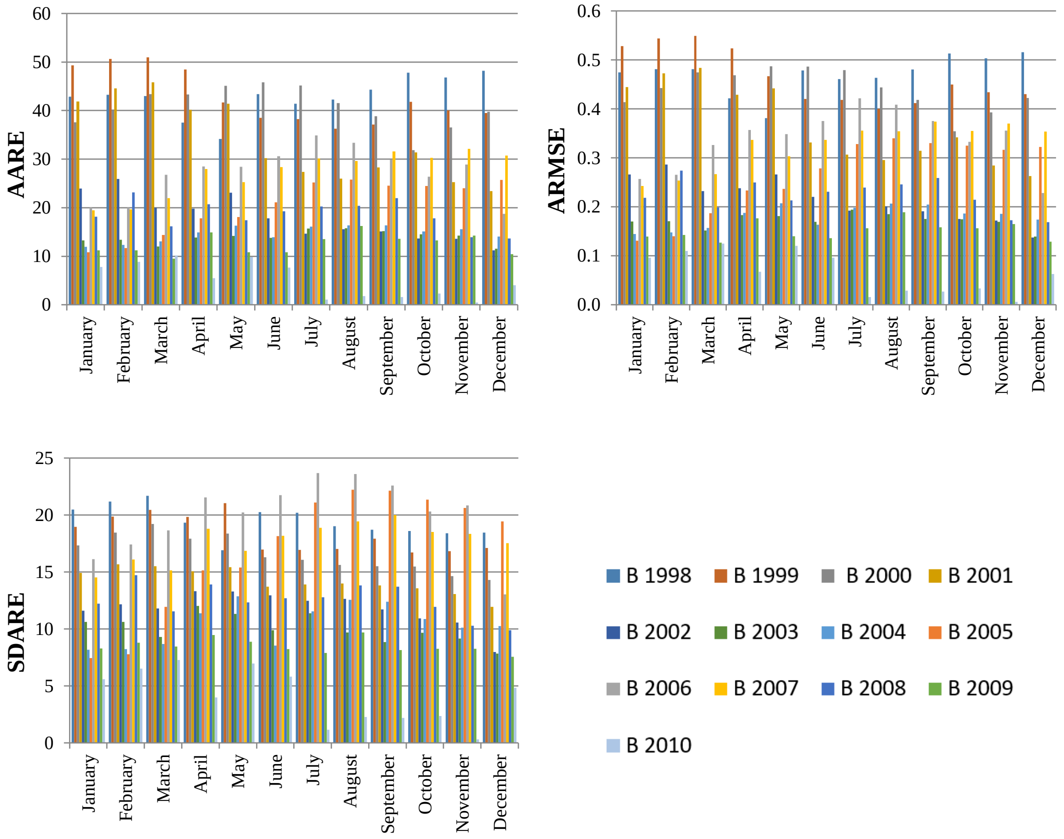


Figure 43: Error values of all calibration simulations for government sector (database 4) using model 2

5.2.4.6 Industrial Sector

Figure 44 illustrates the actual and calibrated monthly water use for industrial sector with different base years. The highest actual consumption is observed in year 2012 in June which has a high temperature (average of 35°C) and scarce in rainfall (average of 0.0 mm), while the lowest actual consumption is observed in the same year in February which has a low temperature (average of 21°C) and it is a rainy month (average rainfall is around 4.3 mm) (AADC and SCAD, 2015).

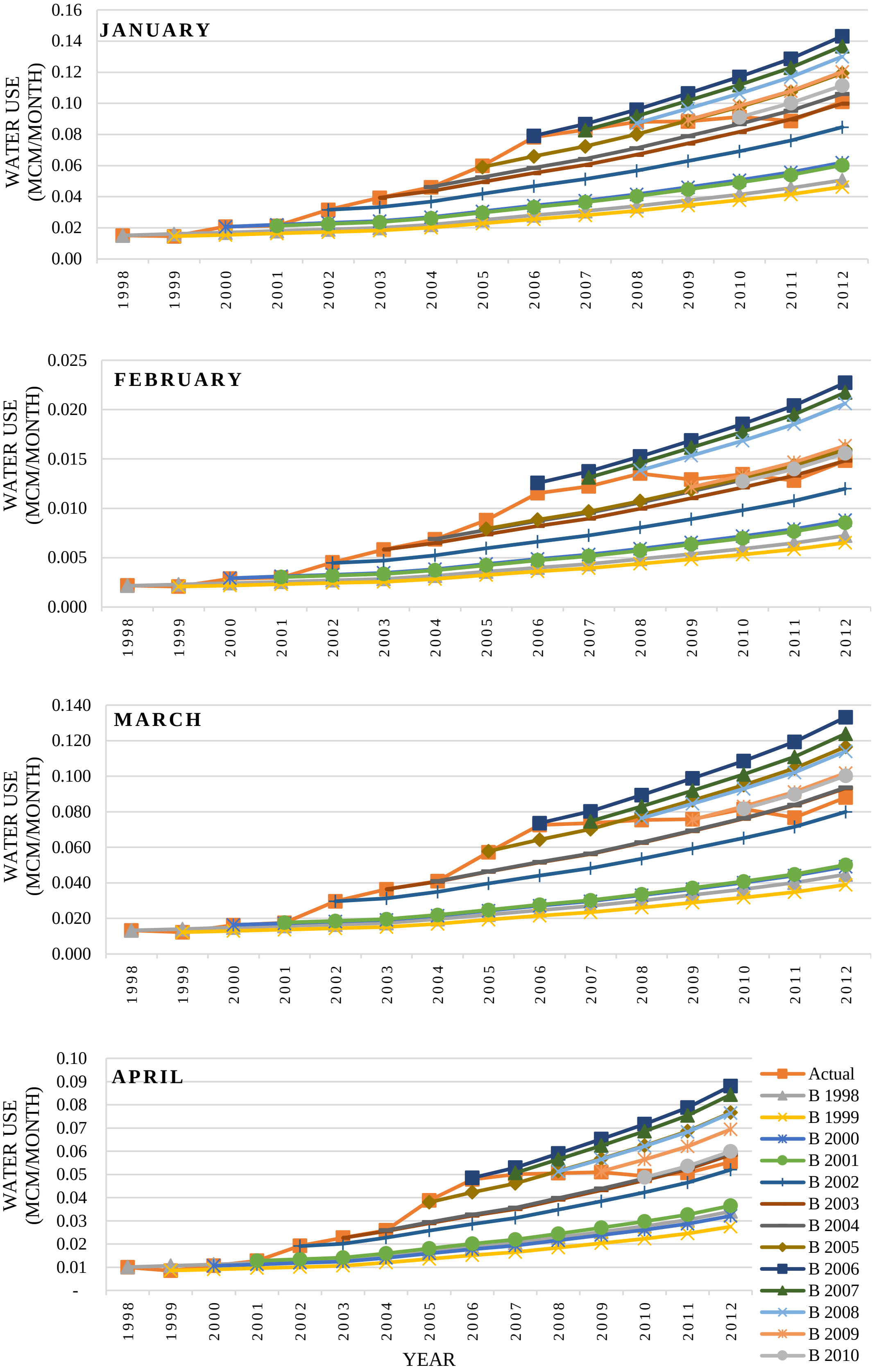


Figure 44: Actual and simulated monthly water use for industrial sector using model 2

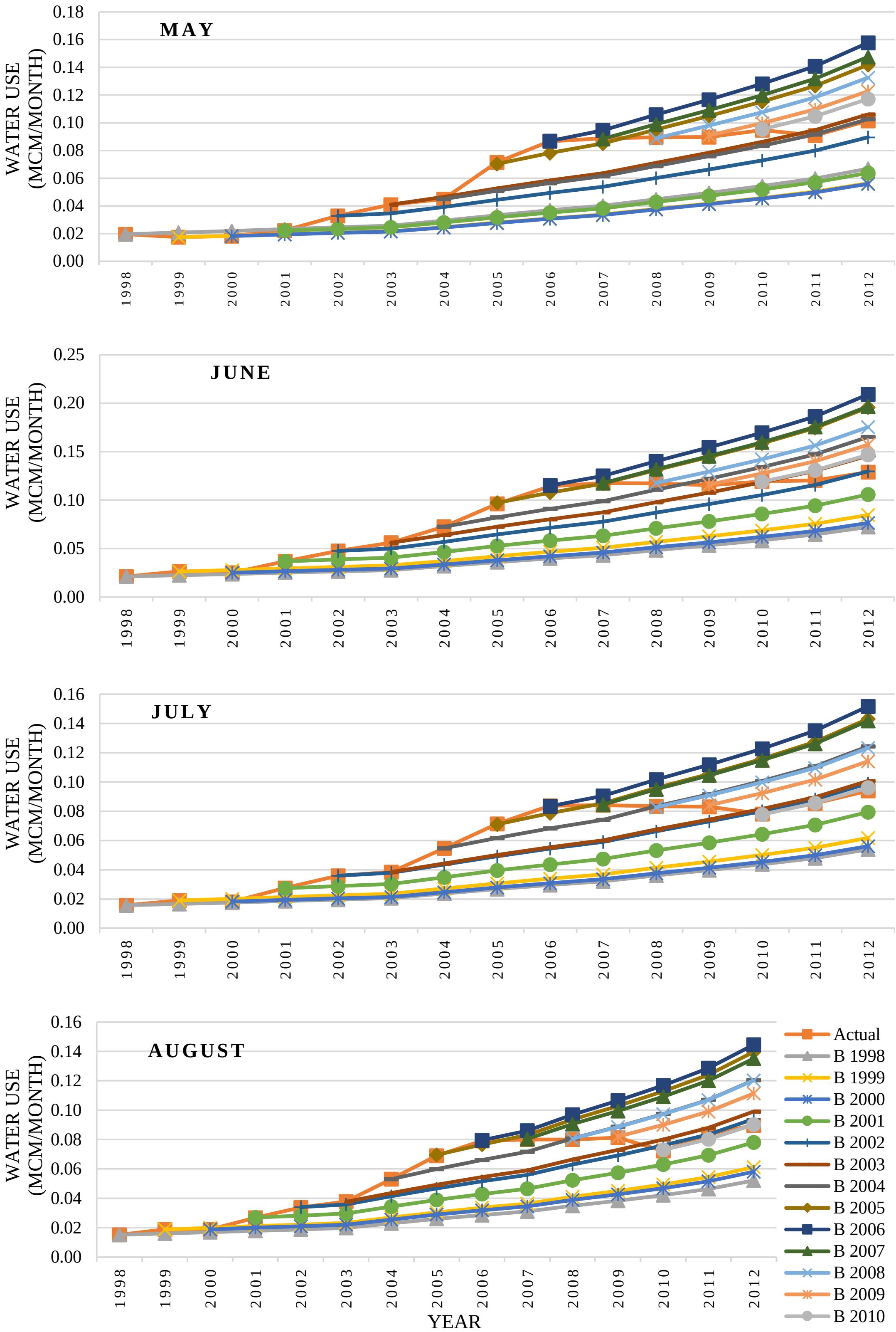


Figure 44: Actual and simulated monthly water use for industrial sector using model 2

(Continued)

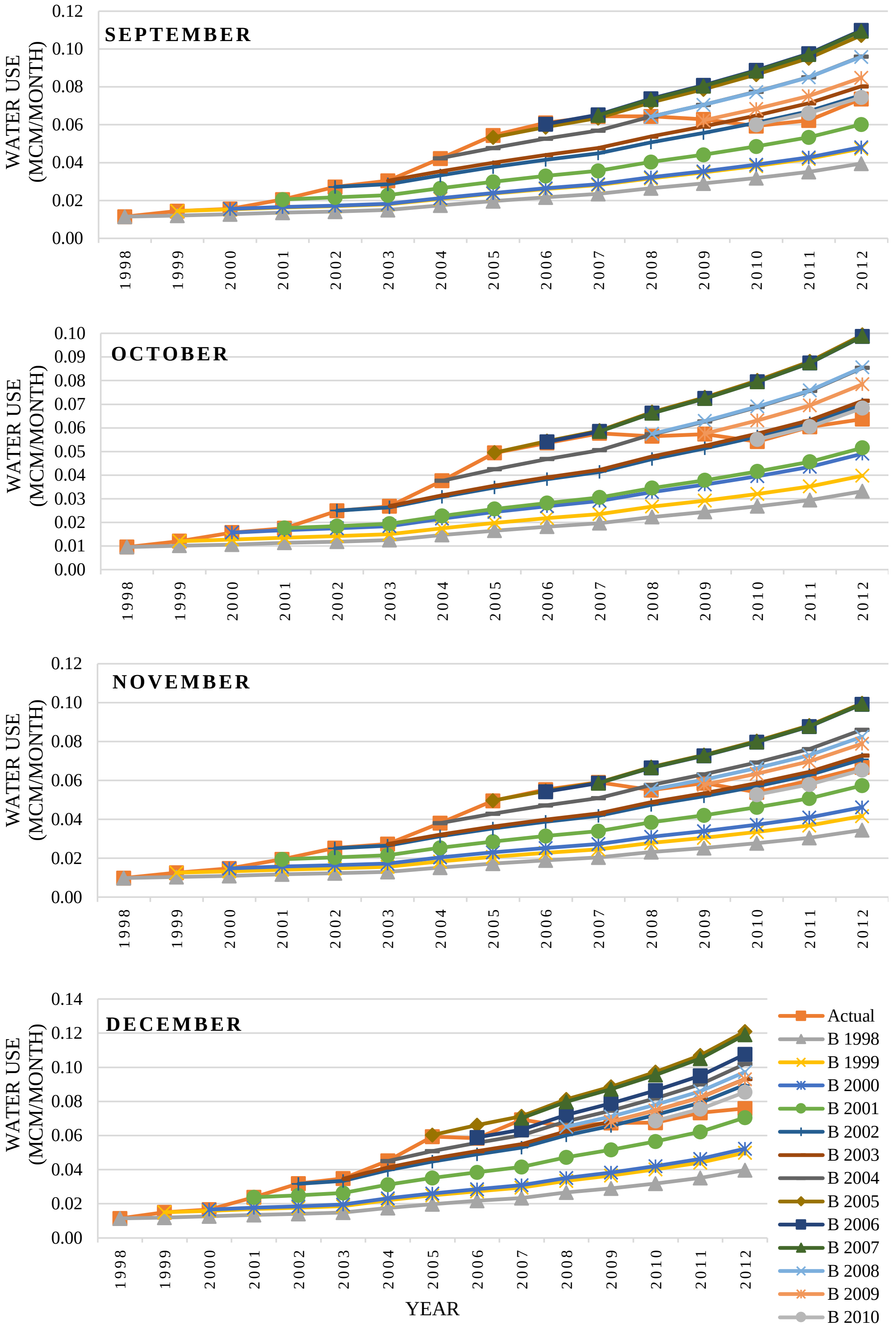


Figure 44: Actual and simulated monthly water use for industrial sector using model 2

(Continued)

Figure 45 presents the AARE, ARMSE, and SDARE for each month for the different base years. Following the same criteria used in previous databases, of choosing the best base year, the calibration simulation with base year 2010 is selected for April, May, and last six months of the year. However, the calibration simulation with base year 2009 is selected for March and June. The base years of 2004 and 2005 are selected for months of January and February, respectively.

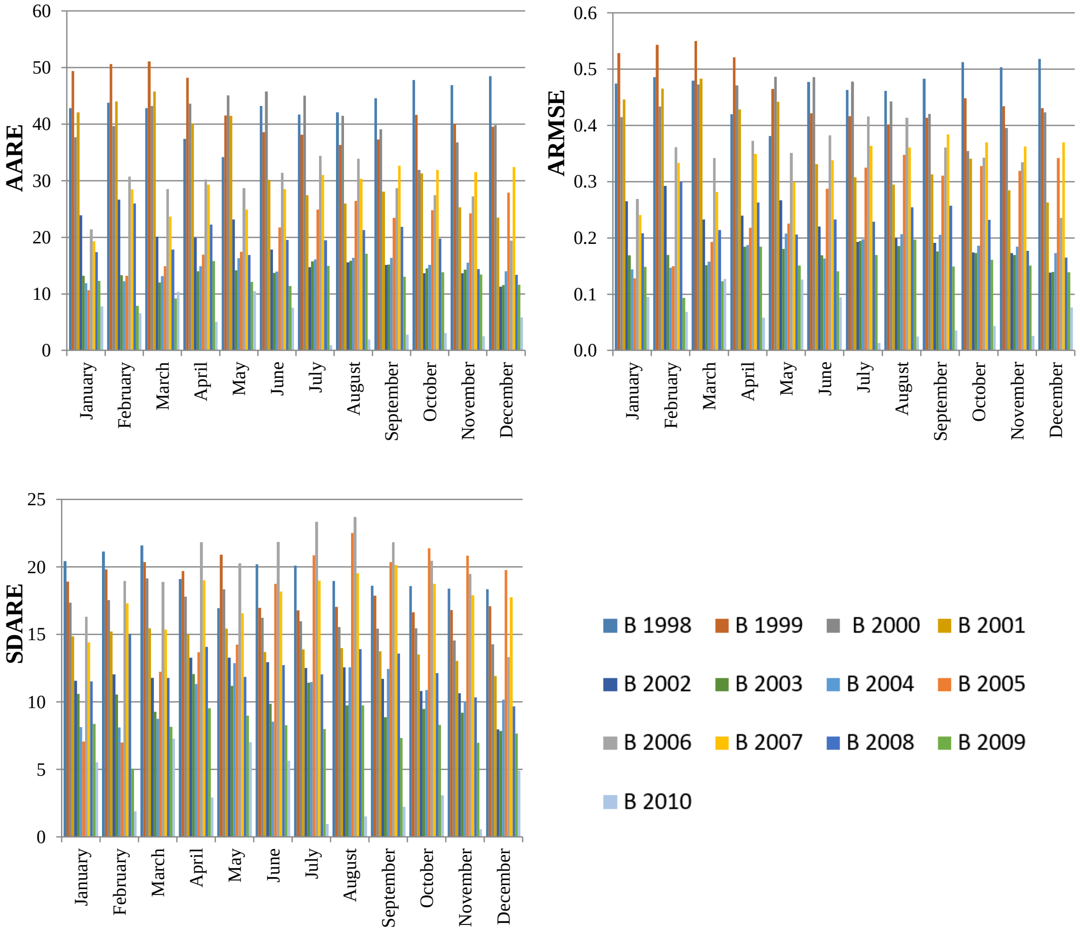


Figure 45: Error values of all calibration simulations for industrial sector (database 4) using model 2

5.2.4.7 Public Services Sector

Figure 46 presents the actual and calibrated water demand for public services sector with different base years. It shows that the highest and lowest actual consumption are observed in year 2012 in months of April (average temperature is 30^{o}C) and February (average temperature is 21^{o}C), respectively (AADC, 2015).

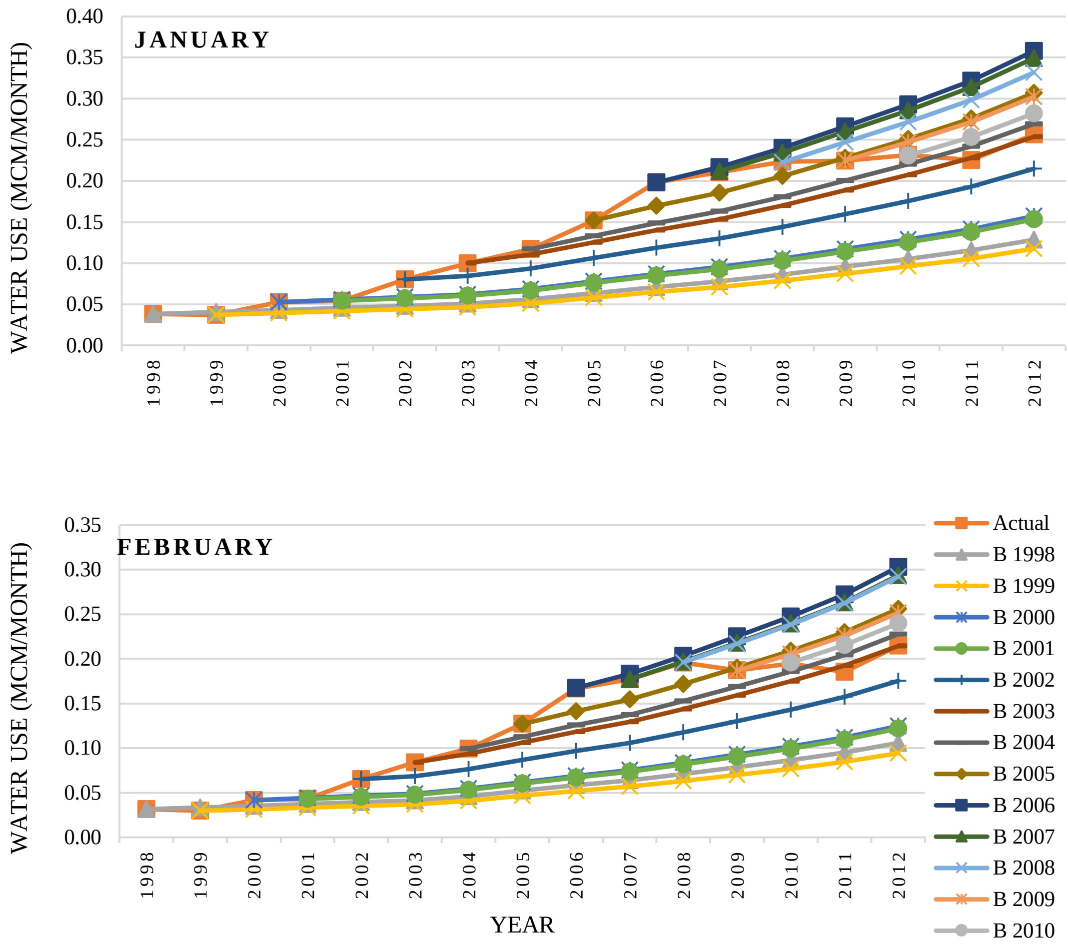


Figure 46: Actual and simulated monthly water use for public services sector using model 2

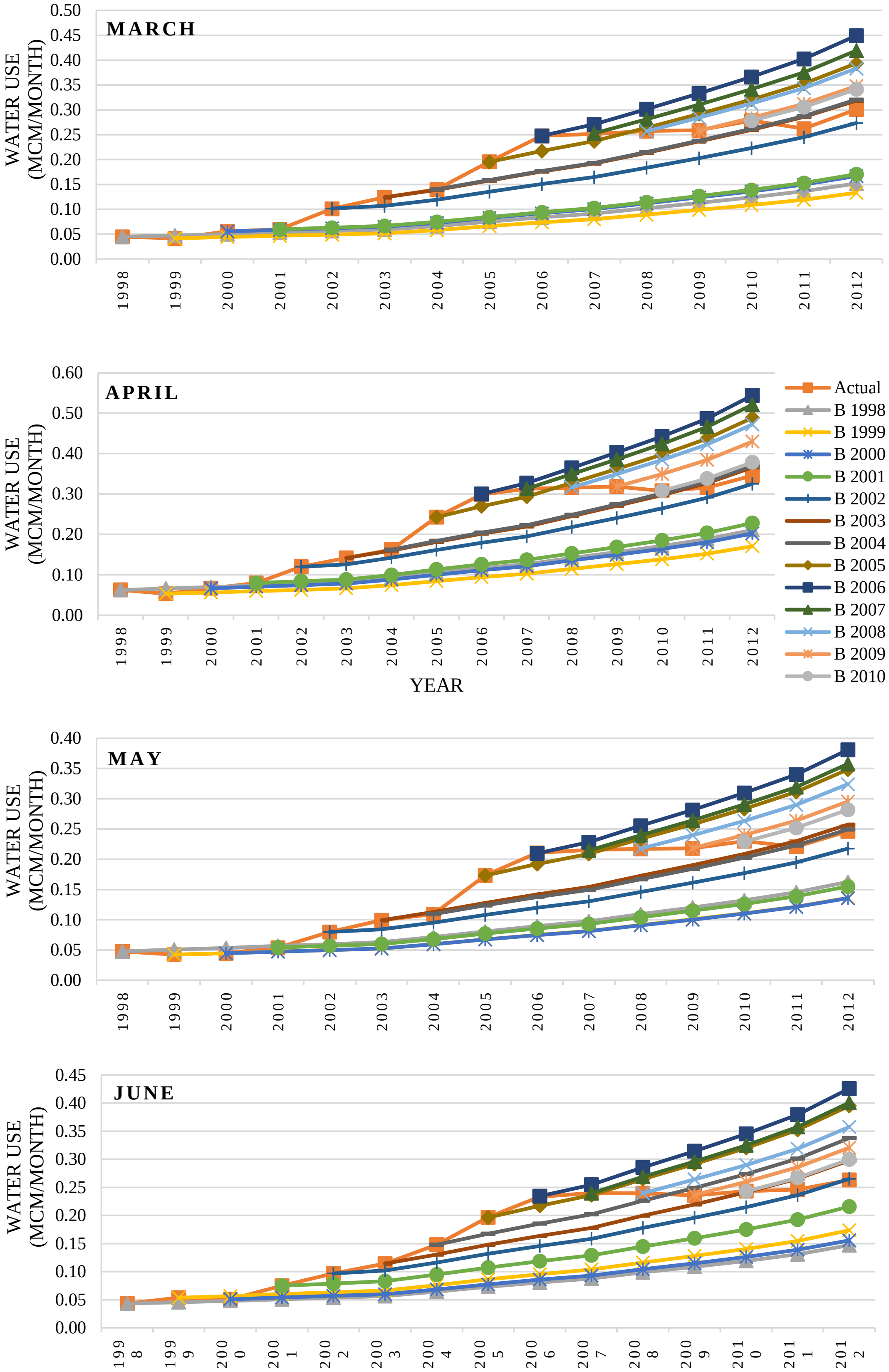


Figure 46: Actual and simulated monthly water use for public services sector using model 2

(Continued)

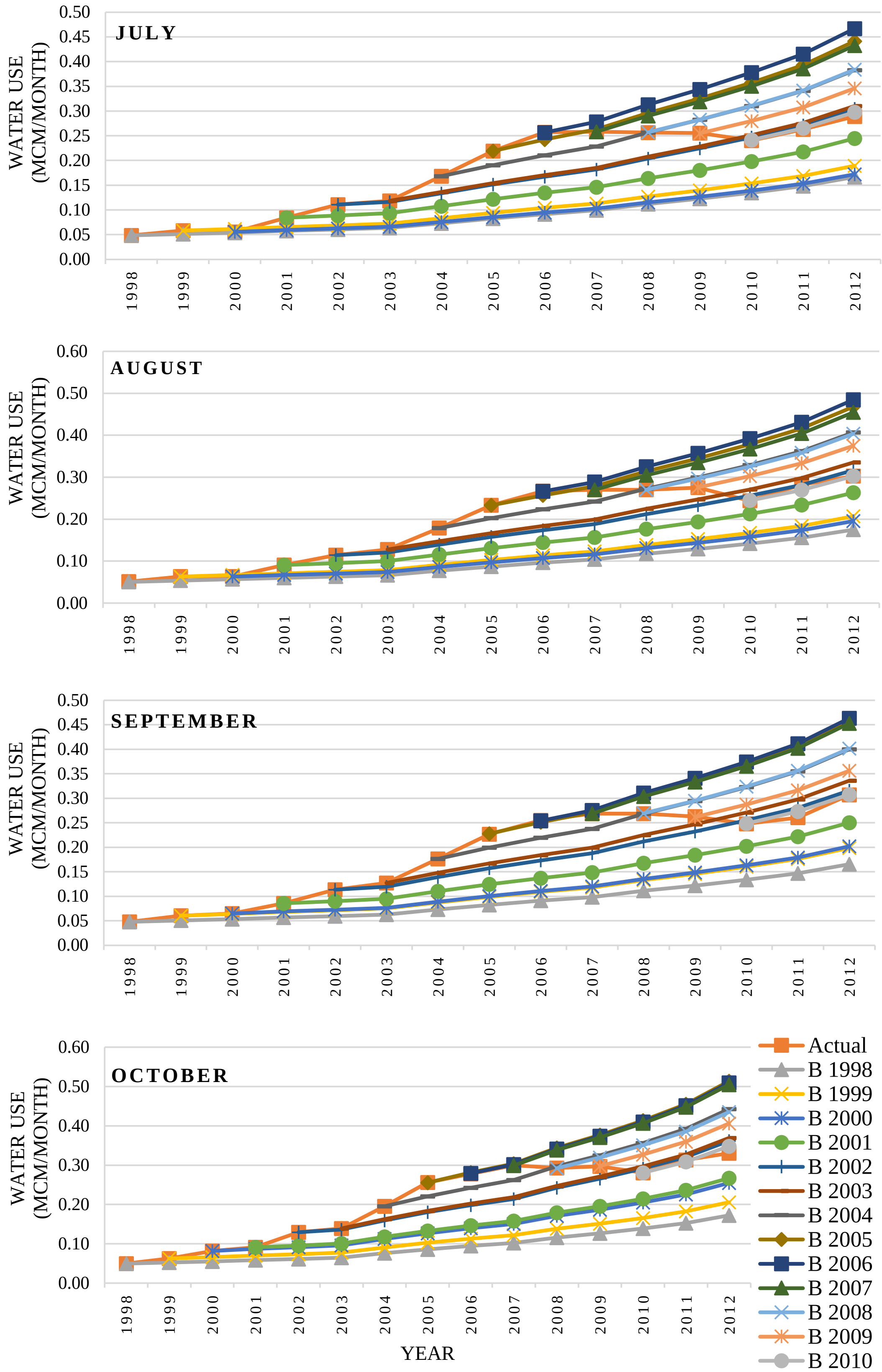


Figure 46: Actual and simulated monthly water use for public services sector using model 2

(Continued)

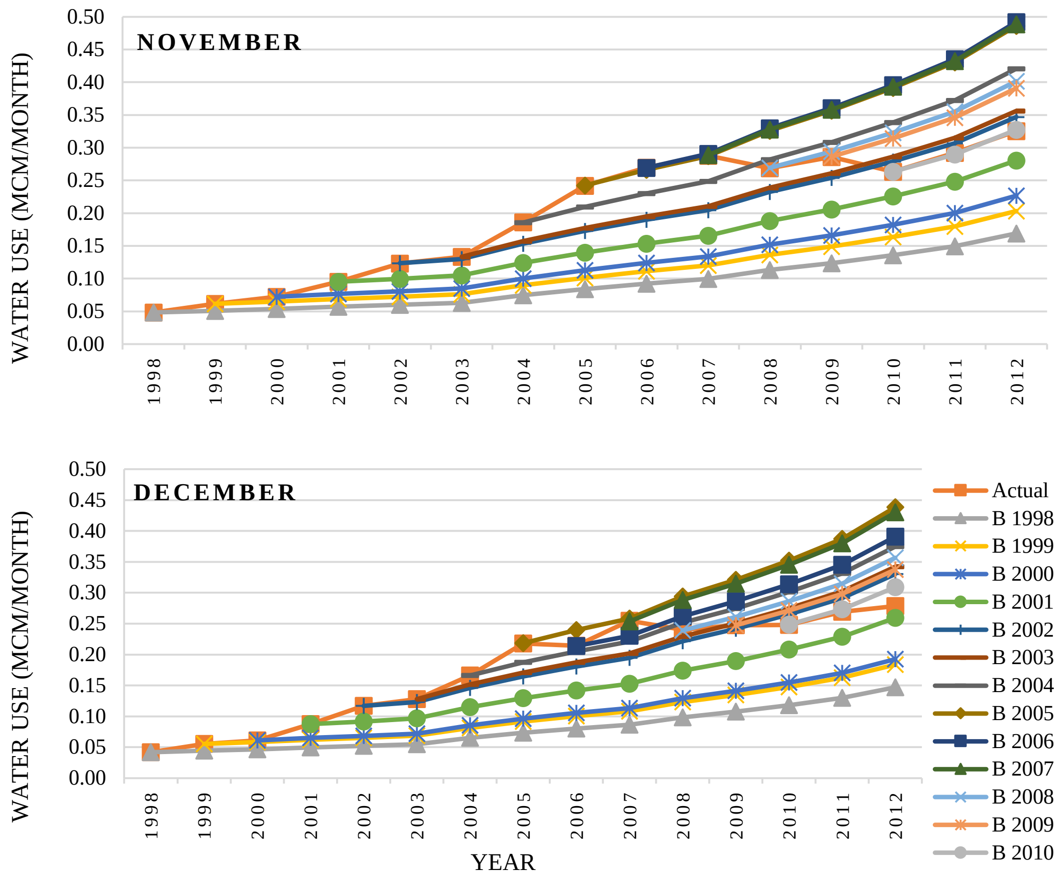


Figure 46: Actual and simulated monthly water use for public services sector using model 2

(Continued)

Figure 47 shows the values of AARE, ARMSE, and SDARE for each month for the different base years. The base year 2010 is selected for April and for last six months of the year. The base year 2009 is selected for March, May, and June. While, the base year 2004 is selected for months of January and February.

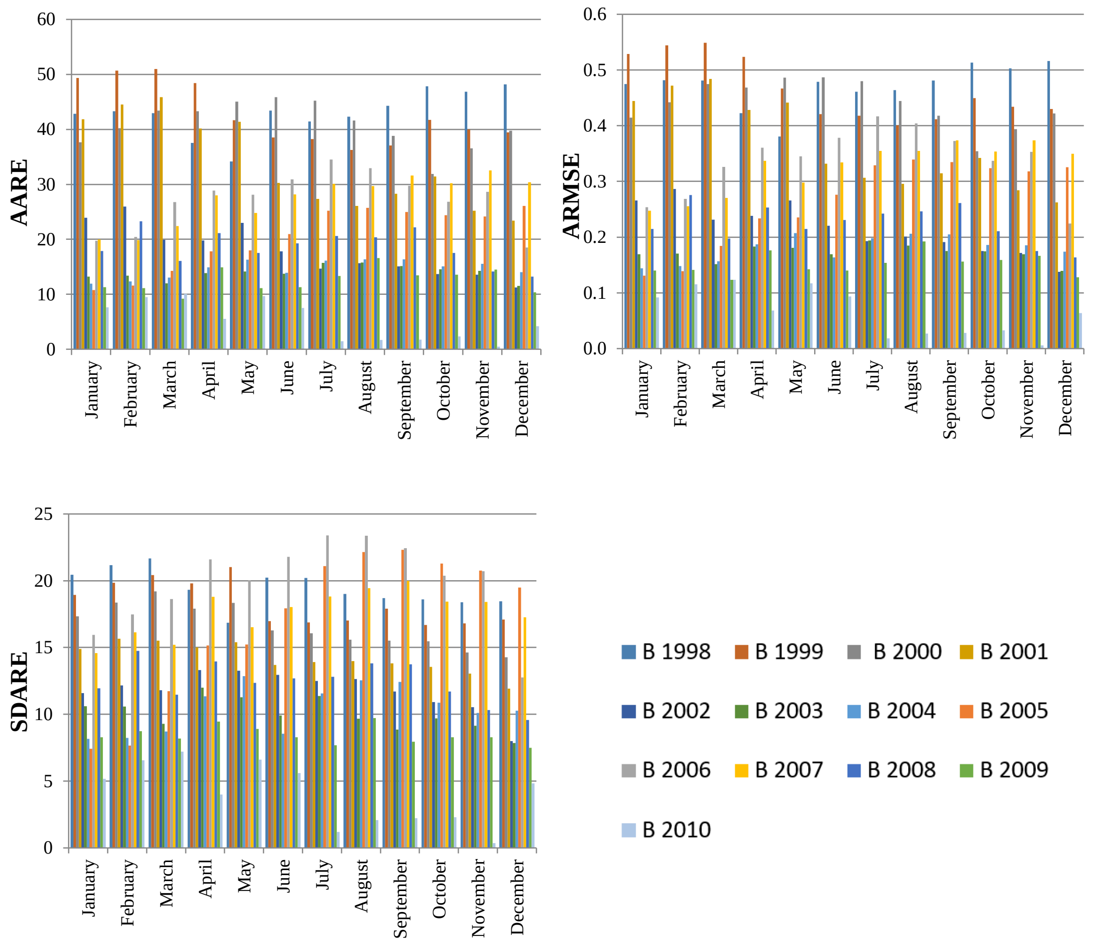


Figure 47: Error values of all calibration simulations for public services sector (database 4) using model 2

The calibration results of database 4 show that all sectors have the same base year except the industrial sector. Table 26 summarizes the best base year for monthly water use for each sector that will be considered for the forecasting scenarios.

Table 26: Best base year for database 4 using model 2

<table>
<tr><th>Month</th><th>Industrial sector</th><th>Other sectors</th><th>Month</th><th>All sectors</th></tr>
<tr><td>January</td><td>2004</td><td>2004</td><td>July</td><td rowspan="6">2010</td></tr>
<tr><td>February</td><td>2005</td><td>2004</td><td>August</td></tr>
<tr><td>March</td><td>2009</td><td>2009</td><td>September</td></tr>
<tr><td>April</td><td>2010</td><td>2010</td><td>October</td></tr>
<tr><td>May</td><td>2010</td><td>2009</td><td>November</td></tr>
<tr><td>June</td><td>2009</td><td>2009</td><td>December</td></tr>
</table>

5.3 Model Verification

The aim of model verification is to ensure that the implementation of the model is correct (Wainer, 2009). Verifications of both models used in this study are conducted with two different base years. Figures 48 and 49 illustrate the verifications of models 1 and 2 using database 1 with base years 2008 and 2010, respectively.

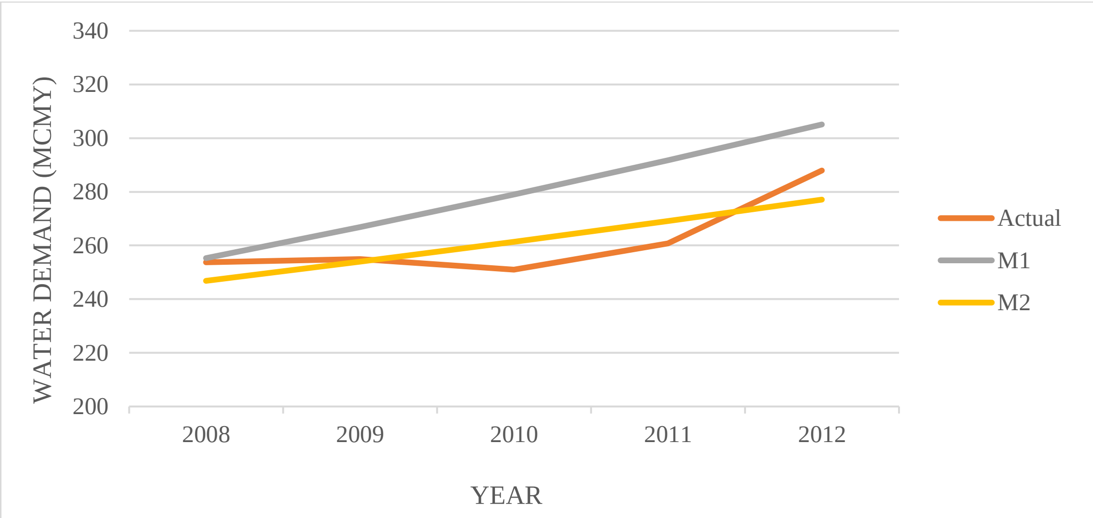


Figure 48: Verification of model 1 and model 2 with base year 2008 (database 1)

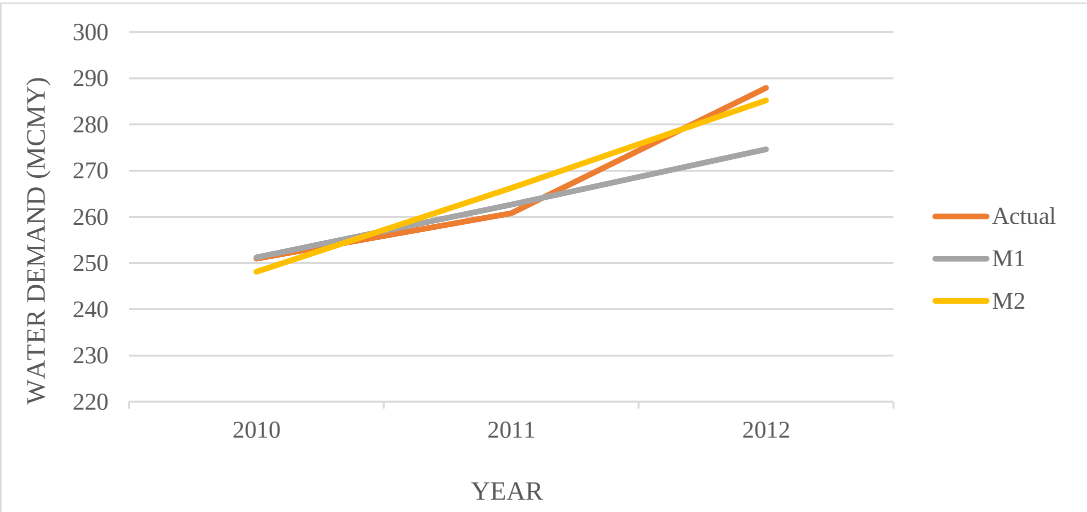


Figure 49: Verification of model 1 and model 2 with base year 2010 (database 1)

Figure 48 shows that the average errors are 7% and 3% for models 1 and 2, respectively, compared with the actual data. On the other hand, Figure 49 shows that the average errors are 2% and 1% for the same two models.

The verification results show that model 2 (linear forecasting model) is more accurate than model 1 (constant use rate model) as previously shown in model calibration. In addition, the results show that the best base year for database 1 using both models is year 2010 as obtained from model calibration.

Chapter 6: Water Demand Forecasting Scenarios

Demand forecasting is the method of estimating future demand of water. The sections of this chapter illustrates three different types of scenarios for forecasting long-term water demands.

6.1 Base Scenarios

The Forecast Manager in IWR-MAIN program can aid water planners in estimating future water demands. The population grows exponentially with time rather than linearly. So, the expected future population was modeled in this study by an exponential regression in SPSS program as shown in Table 27. It was noted that by 2030, the population is expected to increase almost double the current year (2015).

Table 27: Forecasted population from 2013 to 2030 using SPSS program

Year/ Month	January	February	March	April	May	June
2013	639735	640982	642230	643477	644724	645971
2014	663498	666002	668506	671010	673514	676018
2015	694360	696980	699600	702221	704841	707461
2016	726656	729398	732141	734883	737625	740367
2017	760455	763325	766195	769065	771934	774804
2018	795827	798830	801833	804837	807840	810843
2019	832843	835986	839129	842271	845414	848557
2020	871581	874870	878159	881448	884737	888026
2021	912121	915563	919005	922447	925889	929331
2022	954546	958148	961751	965353	968955	972557
2023	998945	1002715	1006485	1010255	1014024	1017794
2024	1045410	1049355	1053300	1057245	1061190	1065135
2025	1094035	1098163	1102292	1106420	1110549	1114677
2026	1144921	1149242	1153562	1157883	1162203	1166524
2027	1198175	1202697	1207218	1211740	1216261	1220783
2028	1253906	1258638	1263370	1268101	1272833	1277565
2029	1312229	1317181	1322133	1327085	1332037	1336989
2030	1373265	1378447	1383629	1388812	1393994	1399176
Year/ Month	**July**	**August**	**September**	**October**	**November**	**December**
2013	647218	648465	649713	650960	652207	653454
2014	678522	681026	683530	686034	688538	691042
2015	710081	712702	715322	717942	720562	723183
2016	743109	745851	748594	751336	754078	756820
2017	777674	780544	783413	786283	789153	792023
2018	813846	816850	819853	822856	825859	828863
2019	851700	854843	857986	861128	864271	867414
2020	891468	894910	898352	901794	905236	908679
2021	932773	936215	939657	943099	946541	949984
2022	976159	979761	983364	986966	990568	994170
2023	1021564	1025334	1029103	1032873	1036643	1040413
2024	1069080	1073025	1076970	1080915	1084860	1088806
2025	1118806	1122934	1127063	1131191	1135320	1139448
2026	1170845	1175165	1179486	1183806	1188127	1192448
2027	1225305	1229826	1234348	1238869	1243391	1247913
2028	1282297	1287029	1291761	1296492	1301224	1305956
2029	1341941	1346893	1351845	1356797	1361749	1366701
2030	1404358	1409541	1414723	1419905	1425087	1430270

6.1.1 Model 1: Constant Use Rate Model

Each subsection below has a certain base year needed to predict future water demand from 2013 to 2030, as following:

6.1.1.1 Database 1

The year 2010 was the selected base year determined by calibration for database 1. Figure 50 shows the total annual water demand forecasting.

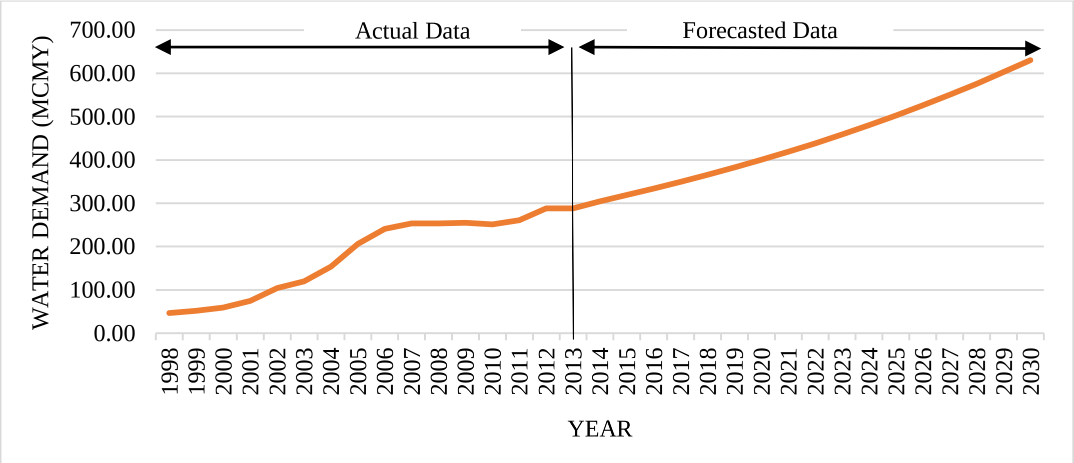


Figure 50: Annual water demand forecasting for database 1 using model 1

From Figure 50, it was found that the estimated water demand in 2030 using the constant use rate model is almost double the current water demand (2015).

6.1.1.2 Database 2

From the calibration, it was found that 2010 is the best base year for database 2. Figure 51 shows the water demand forecasts disaggregated by sector till year 2030.

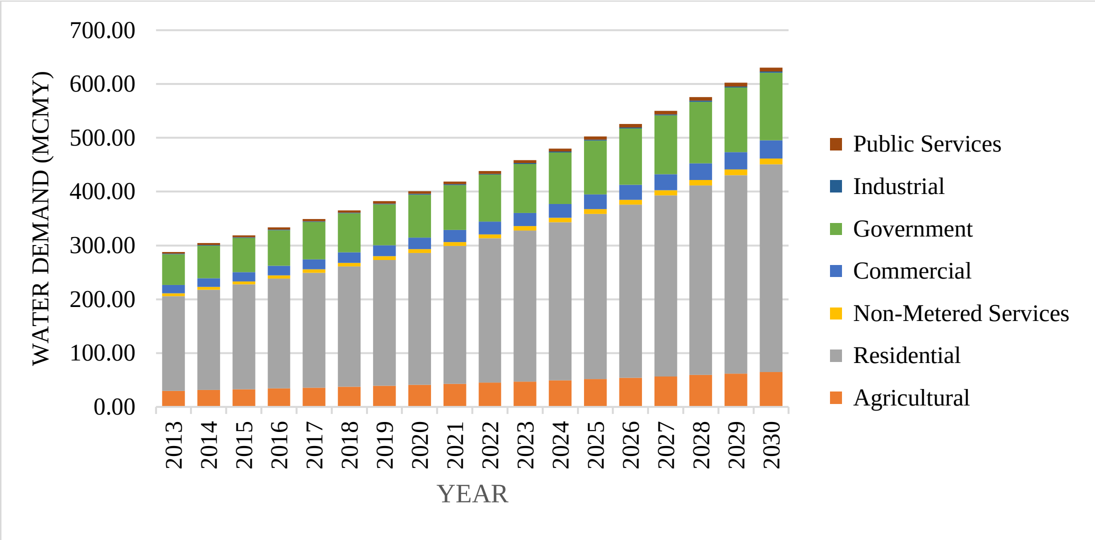


Figure 51: Annual water demand forecasting for database 2 using model 1

Figure 51 shows the result of applying this model to predict water demand for seven different sectors annually. Overall, it shows that the residential sector has the major share of water use with about 61%, then the government sector (20%). On the other hand, the agricultural sector share was about 10% of the total water demand. In addition, other sectors which are commercial, non-metered services, public services, and industrial have around 9% of total water use. This is because the percentage of actual water consumption from 1998 to 2012 was almost constant as shown in Figure 52. Figure 51 shows also that the water demand in year 2030 will be around double the year of 2015 by all sectors.

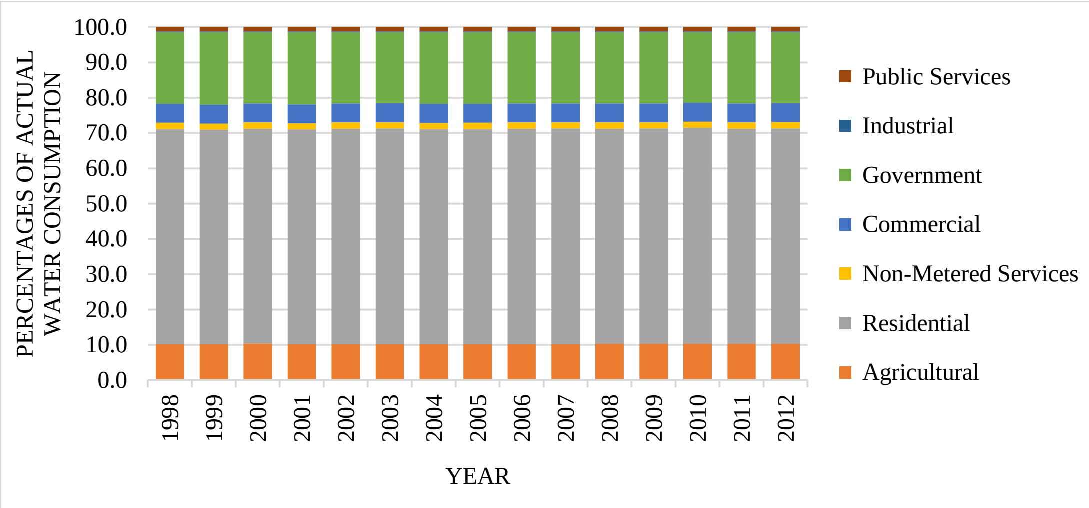


Figure 52: Percentages of actual water consumption

6.1.1.3 Database 3

The total monthly water use was calibrated using constant use rate model. The forecasted water demand was performed by IWR-MAIN program by virtue of base year of each month and the results are displayed in Figure 53.

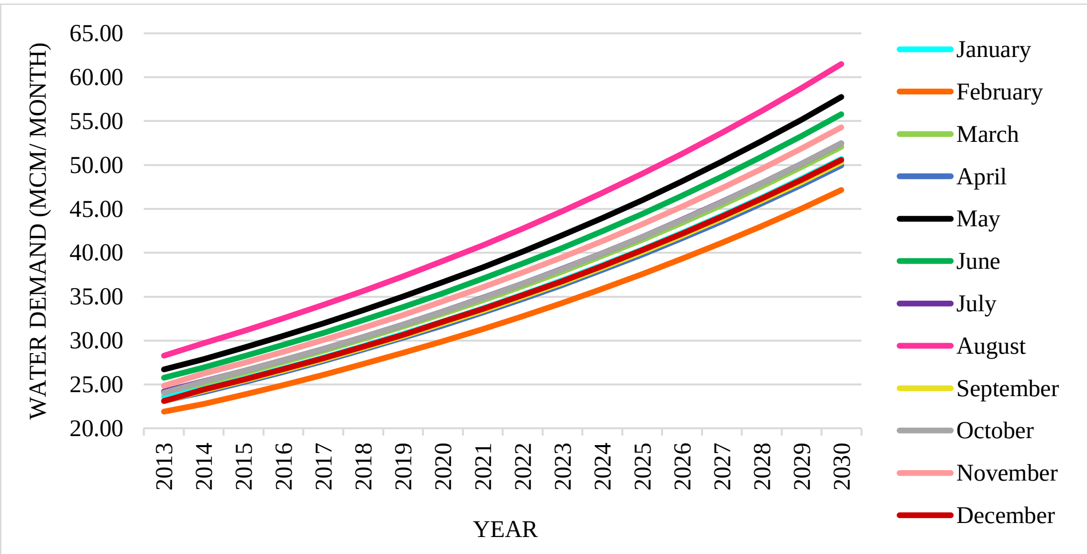


Figure 53: Monthly water demand forecasting for database 3 using model 1

It can be noticed from Figure 53 that water demand in August is higher than others. Water demand was particularly high this month due to the still high temperatures. Whereas, May has the second most water demand. Also, the amounts of water demand in March, July, and October are very close, especially in July and October. The amounts of water demand in January, April, September, and December are almost the same.

6.1.1.4 Database 4

Based on the base years obtained from calibration for database 4, Figure 54 shows the forecasted water demand for each sector. Also, Figure 54 shows that October has the highest water demand for agricultural sector and the least demand for non-metered services and residential sectors. April has the highest water demand for public-services and the least demand for agricultural. March has the highest water demand for residential and the least demand for government. In the residential sector, water is distributed to households for personal use involves drinking, cleaning, and bathing. The water demand in the residential sector is nearly 61% of total water use in Al-Ain city. The commercial, government, and non-metered services sectors show the highest demand in August. The water demand estimates for the commercial sector is almost double the current water demand (2015). For government sector, the difference between the first two highest demands, August and May respectively, is around 66%. This is because all schools and universities have a maintenance work is scheduled before start-school.

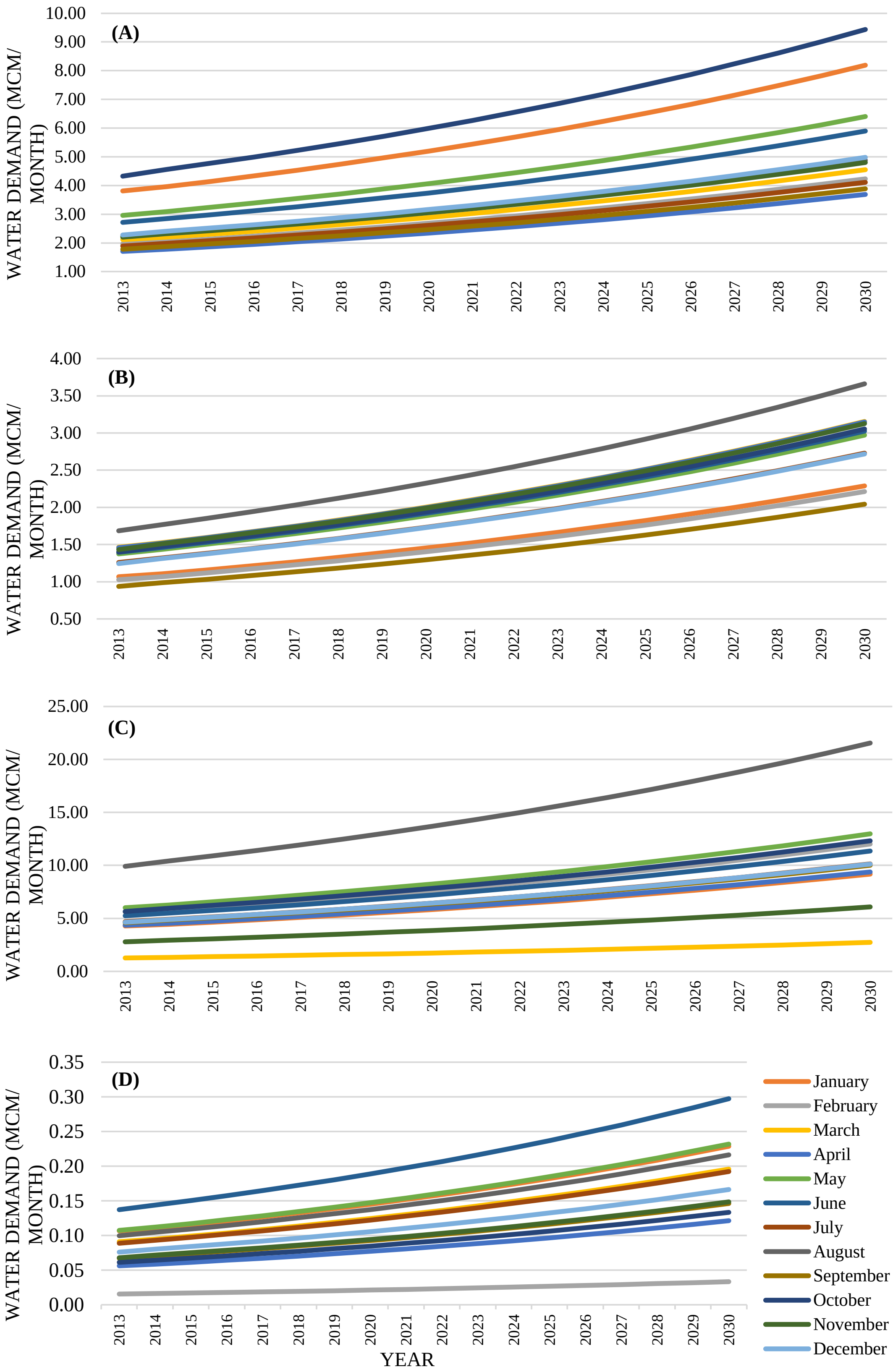


Figure 54: Water demand forecasting monthly for database 4 using model 1 for (A) agricultural, (B) commercial, (C) government, and (D) industrial

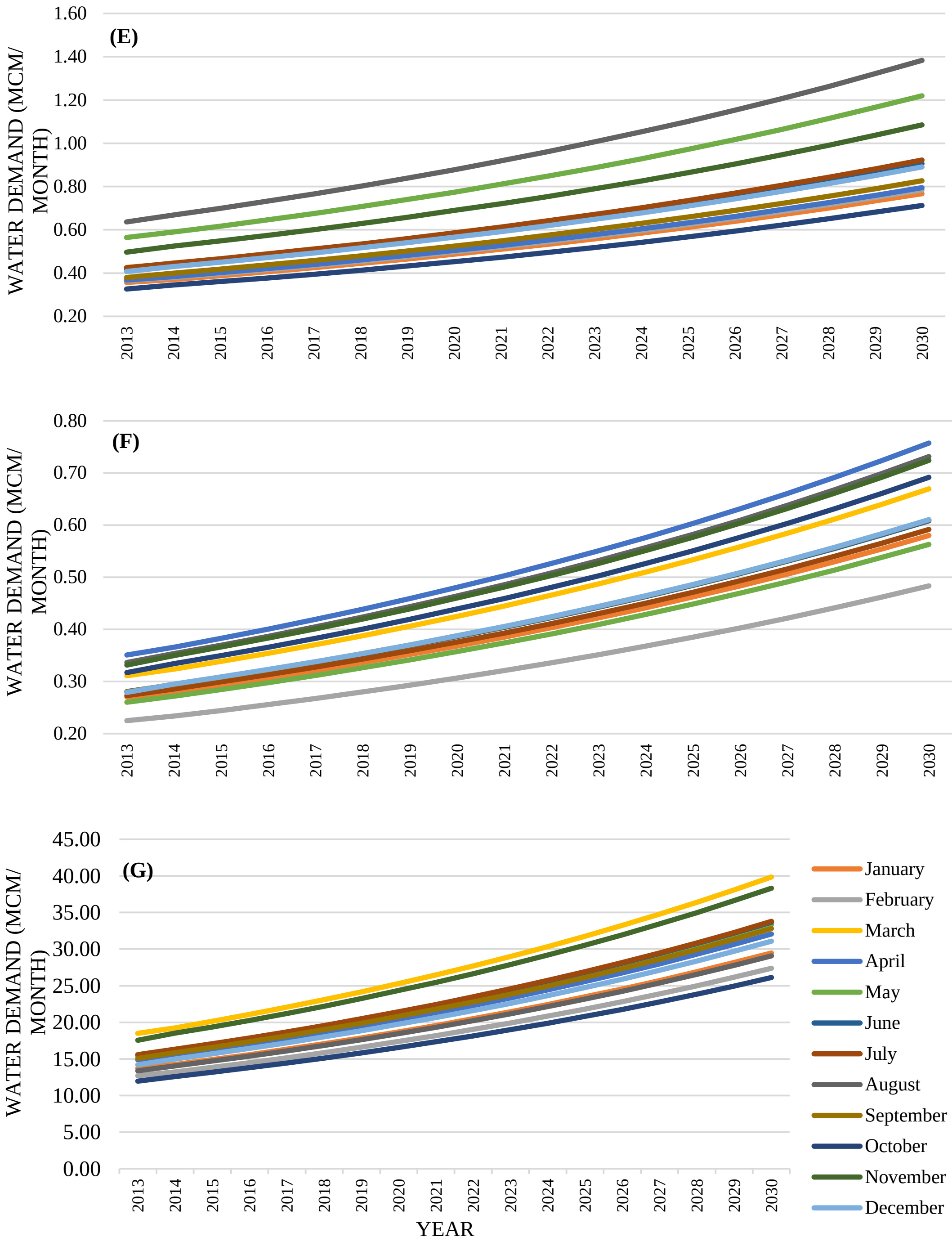


Figure 54: Water demand forecasting monthly for database 4 using model 1 (E) non-metered services, (F) public services, and (G) residential (Continued)

Figure 54 shows also that the least water demand consumes in February for industrial and public-services sectors. For industrial sector, the difference of water quantity between the highest two months is around 30%. The quantity of water demand in June of 2030 is 300,000 cubic meters. This high amount of water demand covers the mega projects that under construction presently. The difference between the least two demands of April and February for industrial sector is high. For public-services sector, the April of 2030 consumes 760,000 cubic meters compared to February of the same year that requires 480,000 cubic meters. Figure 54 also shows that the least water consumed for February and March for industrial and government sectors have almost a constant slope. It presents also that the effect of residential sector of total water demand is the highest, while the industrial sector has the lowest effect of the total water demand.

6.1.2 Model 2: Linear Forecasting Model

This section includes prediction of water demand for seven sectors using linear forecasting model, as follows:

6.1.2.1 Database 1

Database 1 displays the total annual water demand forecasting from 2013 to 2030 as shown in Figure 55.

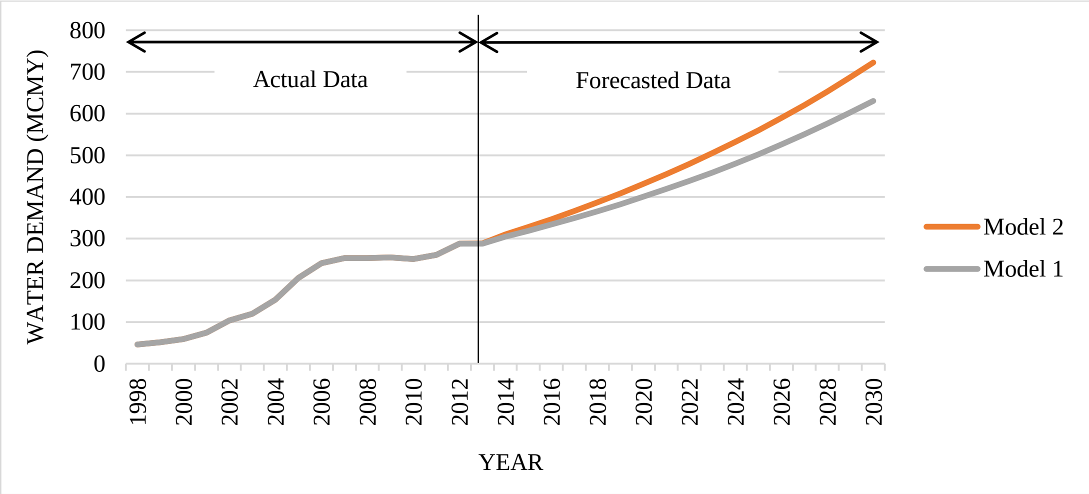


Figure 55: Annual water demand forecasting by database 1 using model 2

Figure 55 illustrates the actual and forested water demand (in million cubic meters per year). It shows that the simulated model 2 is higher than model 1 because the model 2 depends on the model coefficient and intercept (β, α), while model 1 depends directly on the population growth. In 2030, an estimated of 722 million cubic meters per year will be required by model 2. The simulation of model 2 shows that the water demand will increase around of 46% in 2030 compared with 2012, while 40% for the simulation of model 1.

6.1.2.2 Database 2

Database 2 displays the forecasted annual water demand for seven sectors as shown in Figure 56.

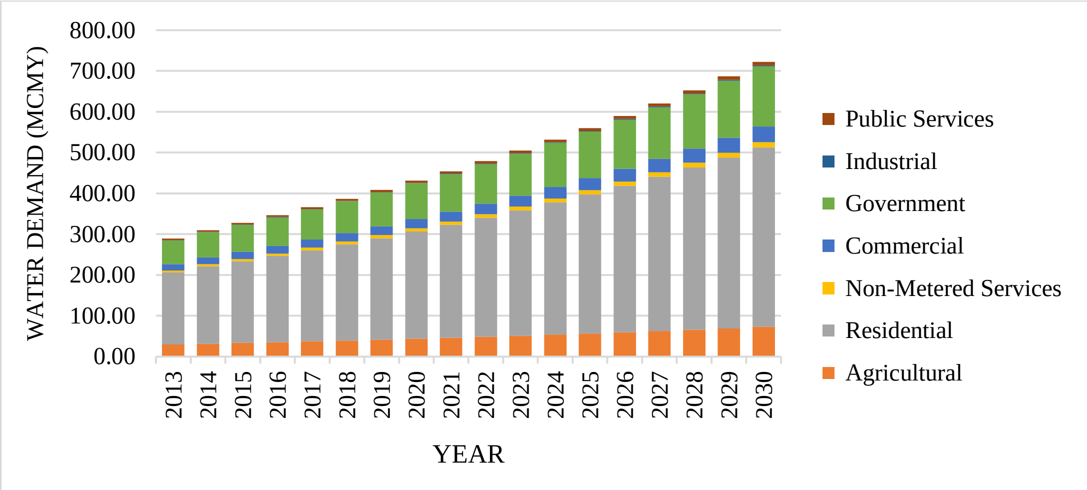


Figure 56: Annual water demand forecasting for database 2 using model 2

The year 2030, residential water demand is the first largest water use category with an estimated 61% of total water demand. The second and third water demand are government and agricultural with an estimated 20% and 10%, respectively. Another 9% are estimated in commercial, non-metered services, public services, and industrial. Figure 56 illustrates the forecasted demand with almost constant ratio because the actual water consumption have a constant ratio.

6.1.2.3 Database 3

Figure 57 illustrates the total monthly water demand. Figure 57 shows that both August and September have the highest amount of water demand. The highest quantity of water demand in August from 2013 to 2025, while in September from 2026 to 2030. December has lower amount of water demand than May during the period of 2013 to 2017 and lower than April during the period of 2017 to 2030. The least quantity of water demand is in June.

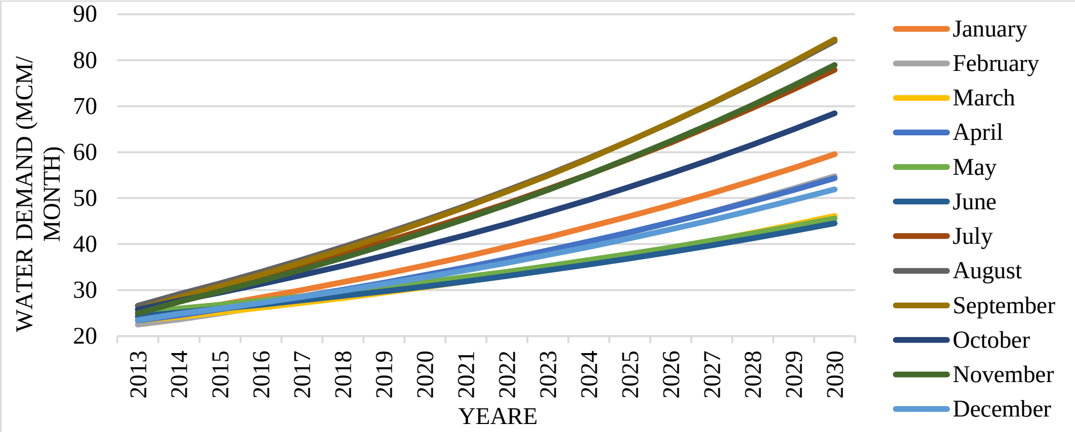


Figure 57: Monthly water demand forecasting for database 3 using model 2

6.1.2.4 Database 4

Figure 58 displays the monthly water demand forecasting for seven sectors. Model 2 simulations depends on the model intercept and coefficient (α, β) so, the water demand of some months does not show a uniformly increasing during the years. Figure 58 shows that the water demand by agricultural sector is estimated the highest amount in October, whereas it is estimated the lowest amount in April. Both commercial and government categories have the highest quantity of water demand in August. The lowest demand shows in March for government sector, while the commercial sector has the lowest demand in February from 2013 to 2023 and in May from 2024 to 2030. November gain the most increasing in water demand by residential and public services sectors. Non-metered services sector has the lowest water demand during from 2017 to 2030 in June, and the highest water demand in August. For industrial sector, June and August have estimated the lowest water demand during the period of 2013-2021 and 2022-2030, respectively; whereas the least quantity of water is in February. Figure 58 also shows that the months display the least demand for government and industrial, March and February respectively, have almost a constant ratio.

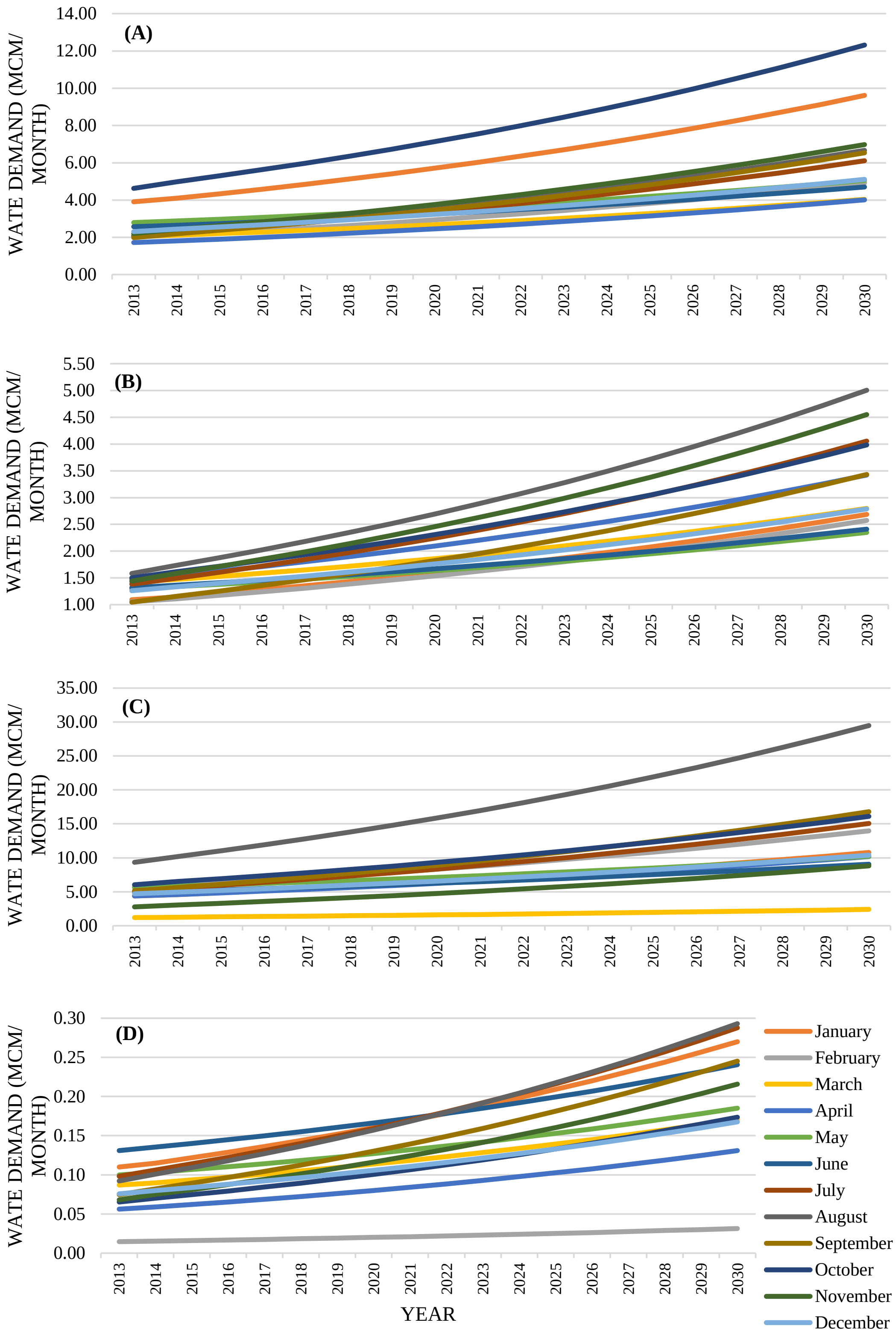


Figure 58: Monthly water demand forecasting for database 4 using model 2 for (A) agricultural, (B) commercial, (C) government, and (D) industrial

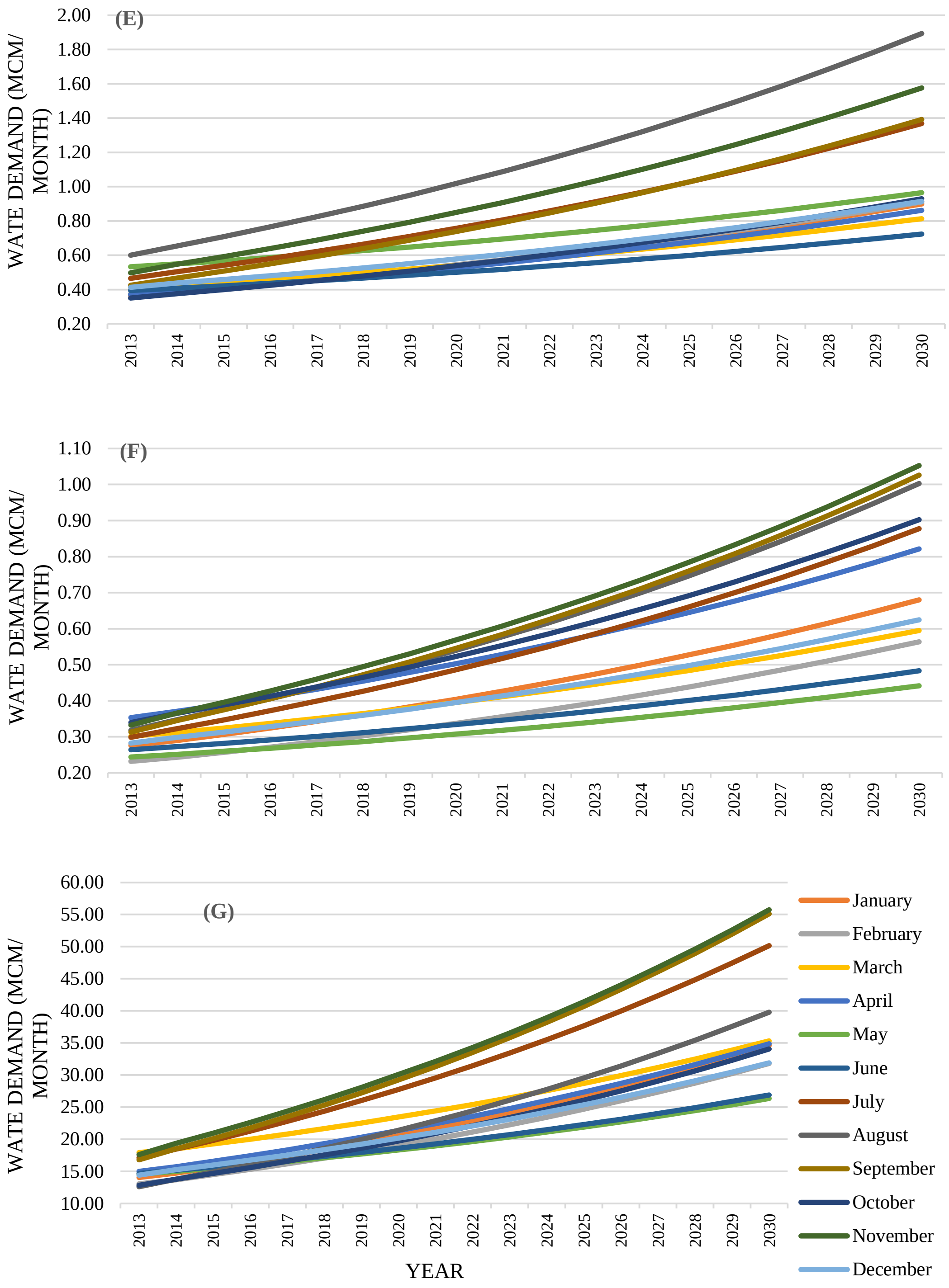


Figure 58: Monthly water demand forecasting for database 4 using model 2 for (E) non-metered services, (F) public services, and (G) residential (Continued)

6.1.3 A Comparison of Models

The results comparison between two forecasting models (Figure 59) shows that model 2 has higher forecasting results than model 1. In both models, the forecasting results using annual databases, database 1 is equal to the results using database 2. While, the forecasting results using monthly databases, database 3 and database 4 are the same. In model 1, monthly databases present higher forecasting results than annual databases of about 1% during the years 2013 - 2030. In model 2, monthly databases present higher forecasting results than annual databases of about 2% in year 2013 and increasing gradually to reach 4% in year 2030. On the other hand, the forecasting results of databases 1 and 2 in model 2 is higher than model 1 by 0.3% in year 2013 and increasing gradually to reach 13% in year 2030. Whereas, the forecasting results of databases 3 and 4 in model 2 is higher than model 1 by 1% in year 2013 and increasing gradually to reach 15% in year 2030. Figure 59 shows also that the water demand forecasting using model 2 is higher than model 1 because the model 2 depends on the amount of water consumption of all the years, while mode 1 depends on the amount of water consumption of base year only.

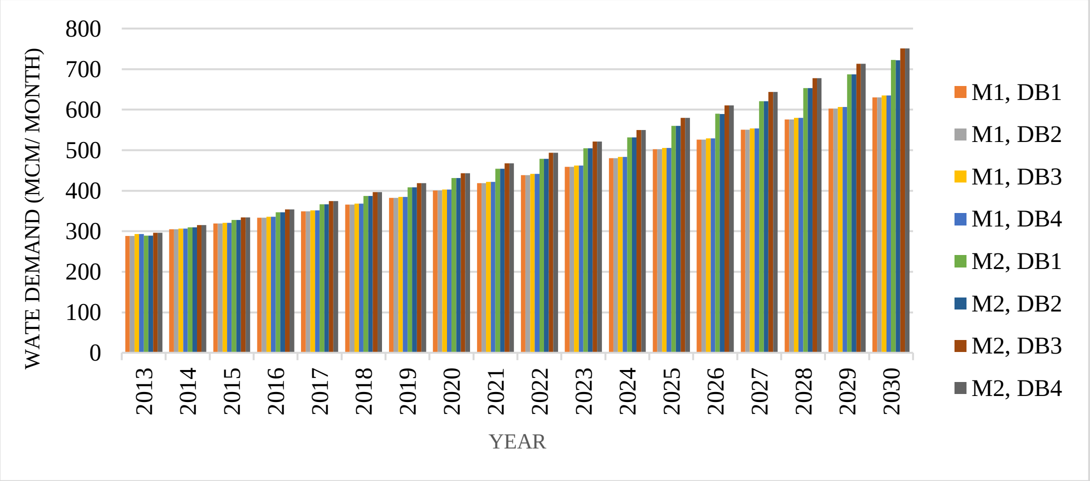


Figure 59: Water demand forecasting using models 1 and 2 for all databases

6.1.3.1 Uncertainty in Predictions

Similar discrepancies between the different databases (as shown in Figure 59) were also noted in measurement of sectoral water use to meter misregistration and incorrect classification of customers (Boland, 2011). Generally, the uncertainty in the projected water demand increases with the increase of projections periods. Long-term water demand forecasting includes several factors such as demographical, environmental, economic, and political. The uncertainty in the forecast of water demand in this study is embedded in the prediction of population growth either yearly or monthly. Therefore, the results depend on the accuracy of the assumptions used to predict population (Hutson et al., 2000). Other source of uncertainty in sectoral water demand is introduced in calculating the model intercept (α) and coefficient (β).

6.2 Population Growth Scenarios

Under this section, comparisons were conducted among three different future scenarios and the base scenario (BS) prediction created by model 2 for database 1. The first scenario discusses the impact of natural population growth on water demand in Al-Ain city. The impact of immigration to cover labor needed for expected mega-projects in Al-Ain city is studied in the second scenario (S2). Al-Ain city is rich with various tourist’s attractions including Al Ain Museum, Al Ain Zoo, Ain Al Fayda Resort, and Al Hili Fun City. In scenarios three and four, the expected visitors to Al-Ain city is considered more specifically, they includes the size of population that obtained from scenario 2 plus the size of tourists which are expected to spend two weeks (S3) or four weeks (S4) in Al-Ain. The projections of total population for the different scenarios are shown in Figure 60.

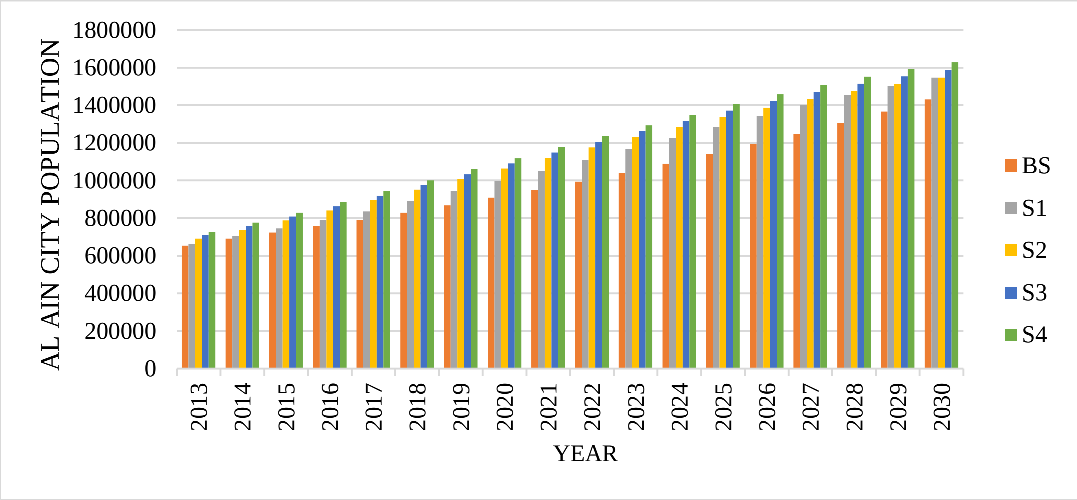


Figure 60: Al Ain city population for the four scenarios

Figure 60 indicates that the population size of residents expected by first scenario is approximately 8% more than the population size expected in base scenario in 2030. This is because the predicted population for base scenario used exponential growth in SPSS, whereas the predicted population for first scenario given by AADC calculated according to the formula:

Predicted population given by AADC = (current estimate of 2005 census population + births - deaths + immigrants - emigrants since 2005 census) (Eq. 14)

The mega projects (scenario 2) have considerably increased the population size and the city visitors estimated as shown in scenario 3. Moreover, as mentioned earlier in Section (5.2.1), the data of regression model intercept and coefficient utilized by base year 2010 were used in these three scenarios to forecast water demand in Al-Ain city from 2013 to 2030 as shown in Figure 61.

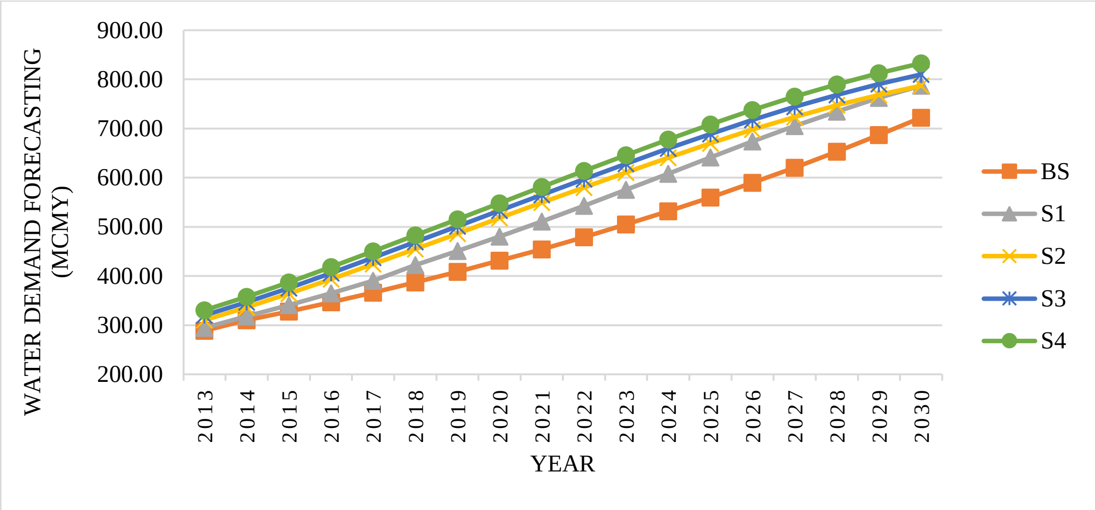


Figure 61: Al-Ain city forecast water demand based on the population growth scenarios

Referring to the Figure 61, it can be easily concluded that the changes in water demand projections are directly proportional to changes in the population size. The water demand projections for the base scenario and the other three scenarios increased in year 2030 by 433, 492, 477 and 490 MCM, respectively, compared to water use in year 2013. Generally, the water demand will increase in 2020, 2025, and 2030 by 1.5%, 2%, and 2.5%, respectively, compared to water use in year 2013. Figure 61 also shows that the difference between the base scenario and scenario 1 is almost 10% and 8% in year 2020 and 2030, respectively. The water demand based on scenario 2 represents that the mega developments require in year 2020 by 16.5% more than water demand in the base scenario due to increase number of workers and the demand will decrease to 8% in 2030 because the end work in construction. Scenario 4 has 2.8% increase of water demand more than Scenario 3, this is because the development plan for Al-Ain city till year 2030 is focus in tourism so, the volume of visits is expected to increase.

6.3 Water Losses Scenarios

This second set of scenarios includes ten different water losses sub-scenarios. Data received from Al-Ain Distribution Company (AADC) indicates that losses through the water distribution in Al-Ain city is around 20%. Table 28 displays the water demand excluding the distribution losses.

Table 28: Amount of water demand forecast and losses (MCMY)

Year	Water production	Water demand = 80%	Losses = 20%
2015	327.91	262.33	65.58
2016	346.67	277.33	69.33
2017	366.30	293.04	73.26
2018	386.84	309.47	77.37
2019	408.34	326.67	81.67
2020	431.36	345.08	86.27
2021	454.39	363.51	90.88
2022	479.03	383.23	95.81
2023	504.82	403.86	100.96
2024	531.81	425.45	106.36
2025	560.05	448.04	112.01
2026	589.61	471.69	117.92
2027	620.54	496.43	124.11
2028	652.91	522.33	130.58
2029	686.79	549.43	137.36
2030	722.24	577.79	144.45

Table 29 highlights the ten sub-scenarios that contain the expected percentages of water lost from the distribution system. The first nine scenarios involve different cases; increased water losses 1% per 3 years, 2% per 3 years, and 1% per 1 year. For the first three scenarios (S5, S6, and S7) are expected no rehabilitation of water distribution systems, so the water losses increase until reach in 2030 to 25%, 30%, and 35%, respectively, from total water demand. For the other seven sub-scenarios are expected to rehabilitate water pipes in year 2015, and the reduction of water losses is expected till year 2020 for scenarios (8, 9, and 10) and till year 2025 for scenarios (S11, S12, and S13). Continuing with 10% of water losses to be reached in 2030 is built in scenario 14. Shifting water losses from 20% from total water demand in 2015 to 10% in 2030 is shown in scenario14 in order to drop in total demand compared to previous scenarios.

Table 29: Water losses percentage for different scenarios

Year	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14
2015	20%	20%	20%	20%	20%	20%	20%	20%	20%	20%
2016	20%	20%	21%	18%	18%	18%	19%	19%	19%	19%
2017	20%	20%	22%	16%	16%	16%	18%	18%	18%	18%
2018	21%	22%	23%	14%	14%	14%	17%	17%	17%	17%
2019	21%	22%	24%	12%	12%	12%	16%	16%	16%	16%
2020	21%	22%	25%	10%	10%	10%	15%	15%	15%	15%
2021	22%	24%	26%	11%	12%	11%	14%	14%	14%	14%
2022	22%	24%	27%	11%	12%	12%	13%	13%	13%	14%
2023	22%	24%	28%	11%	12%	13%	12%	12%	12%	13%
2024	23%	26%	29%	12%	14%	14%	11%	11%	11%	13%
2025	23%	26%	30%	12%	14%	15%	10%	10%	10%	12%
2026	23%	26%	31%	12%	14%	16%	11%	12%	11%	12%
2027	24%	28%	32%	13%	15%	17%	11%	12%	12%	11%
2028	24%	28%	33%	13%	15%	18%	11%	12%	13%	11%
2029	24%	28%	34%	13%	15%	19%	12%	14%	14%	10%
2030	25%	30%	35%	14%	16%	20%	12%	14%	15%	10%

Figure 62 indicates the water demand forecast from year 2015 to 2030 for all water losses scenarios.

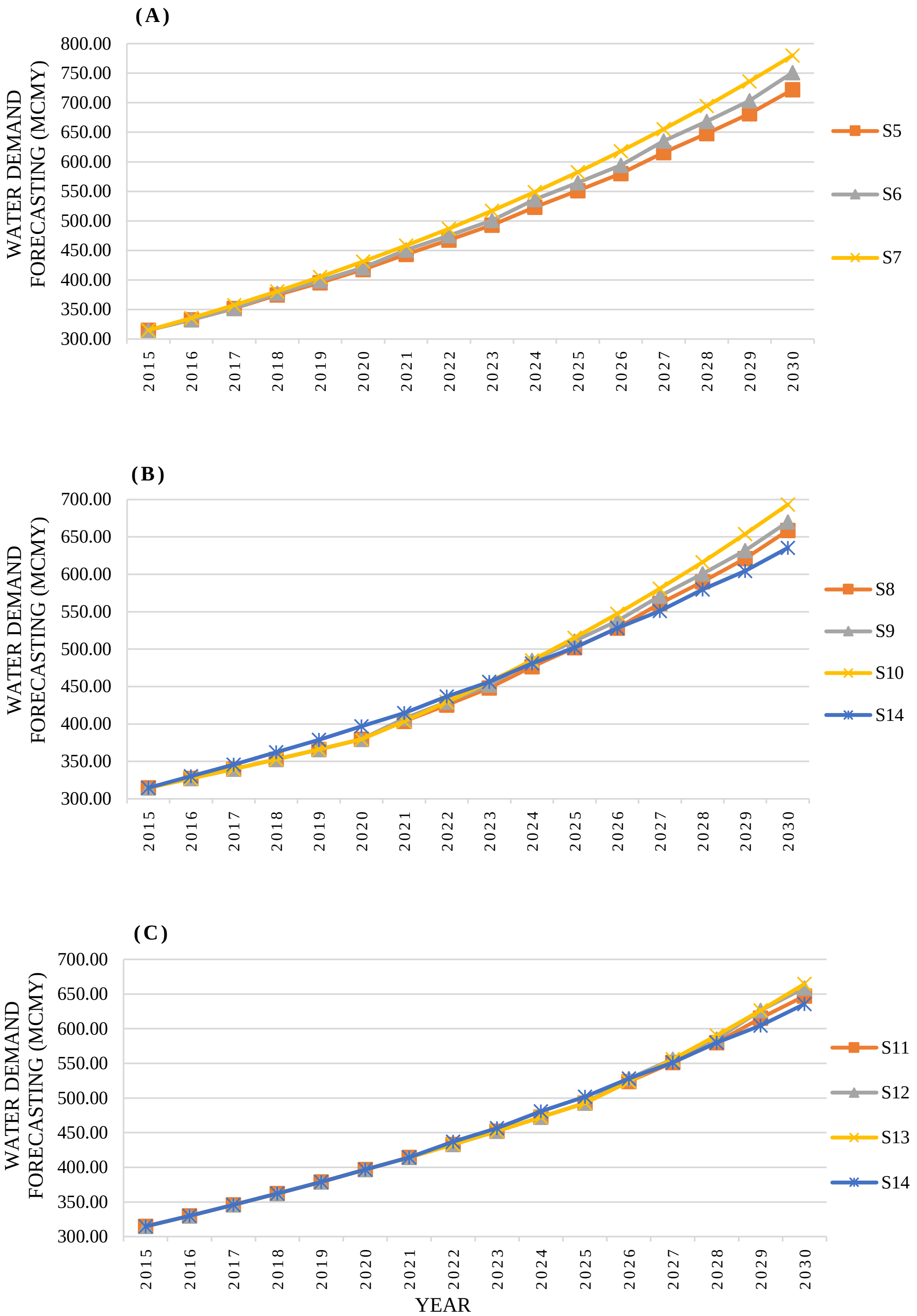


Figure 62: Water demand based on the water losses scenarios

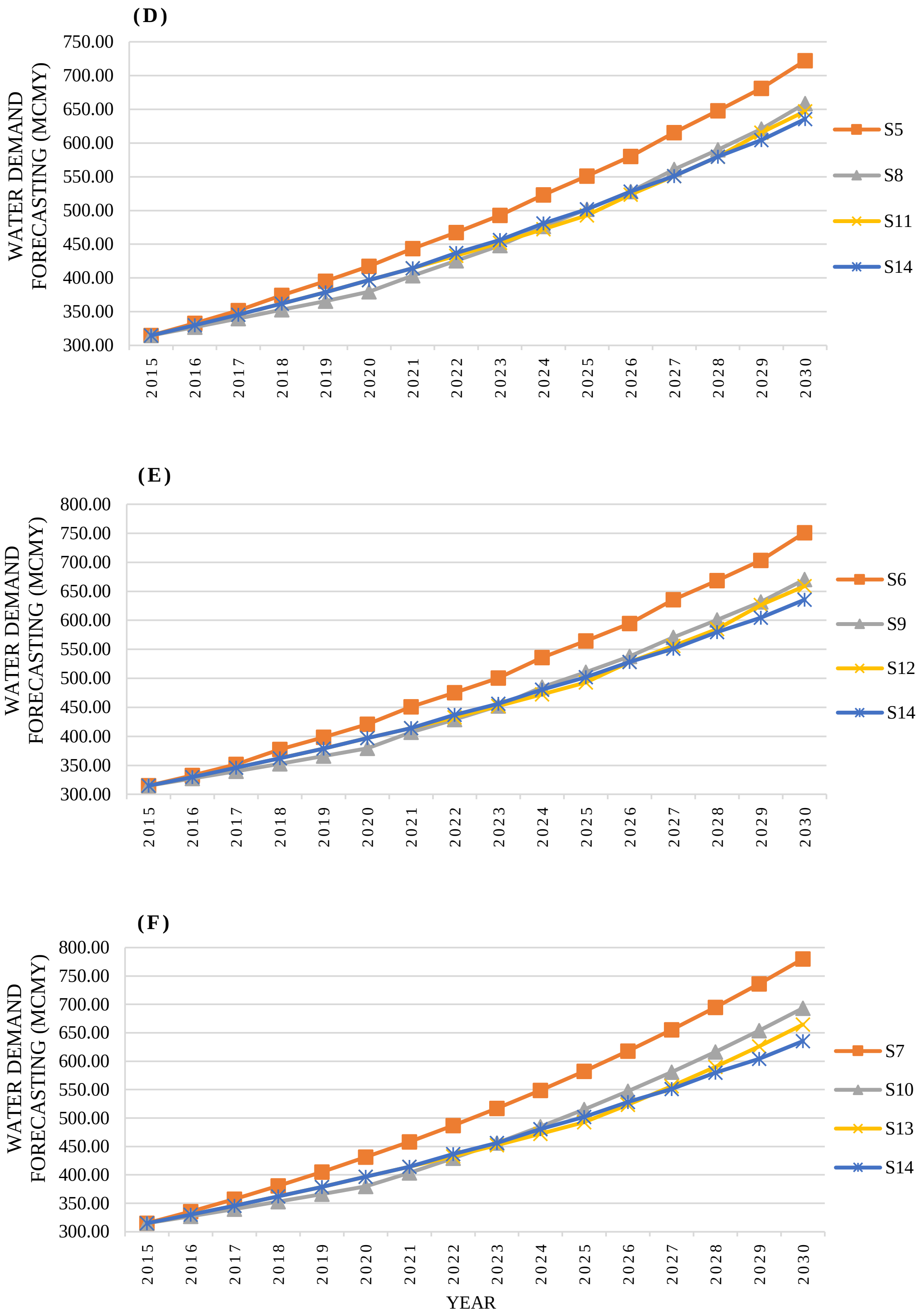


Figure 62: Water demand based on the water losses scenarios (Continued)

Referring to the Figure 62, the graph indicates that the amount of water demand is directly proportional to increase amount of water losses. Generally, the highest water demand is considered in scenario 7 during all years due to high increase in water losses. Figure 62B shows that scenario 14 has the highest water demand till year 2023 and then drops to become the least in year 2030, while scenario 10 is the highest from 2024 to 2030. Figure 62C displays that the four scenarios contain same amount of water demand for the first seven years, and scenario 14 has the least demand for the last two years. Figures 62D, E, and F show the high difference between S5, S6, and S7 and the other scenarios. Overall, Figure 62 demonstrates that the improvement conducted for scenario 14 does not contain the least quantity of water demand except from 2027 to 2030. According to the first nine scenarios, the minimum amount of water demand is obtained from scenarios 8, 9, and 10 during 2016 – 2022, also from scenario 8 in 2023. The lowest water demand by scenarios 11, 12, and 13 are obtained in year 2025. Scenario 11 has the lowest water demand during from 2026 to 2028, also scenario 13 has the lowest demand in 2026.

Chapter 7: Water Budget Model

The main objective of this chapter is to develop a water budget model to assess water use patterns in Al-Ain region to know the principles behind the sources of water and to understand the hydrological components like evaporation, precipitation, runoff and surface flow.

The water supply in Al-Ain depends on three main sources; namely groundwater, desalinated water, and recycled water. These three sources of water must be allocated and managed efficiently to meet the requirements of agriculture, commercial, industrial, governments, residential, public services, and non-metered services to ensure conservation of non-renewable resources. The UAE is among the highest producers desalinated water globally, because of the high water consumption, the shortage of natural water resources, the deficiency of rainfall with high temperatures, and high in the evaporation rates.

Figure 63 illustrates the peak daily water supply of Abu-Dhabi Emirate from year 1999 to year 2013. It displays the largest amount of water supplies to Abu-Dhabi Emirate, while a few amount of water is exports to other emirates.

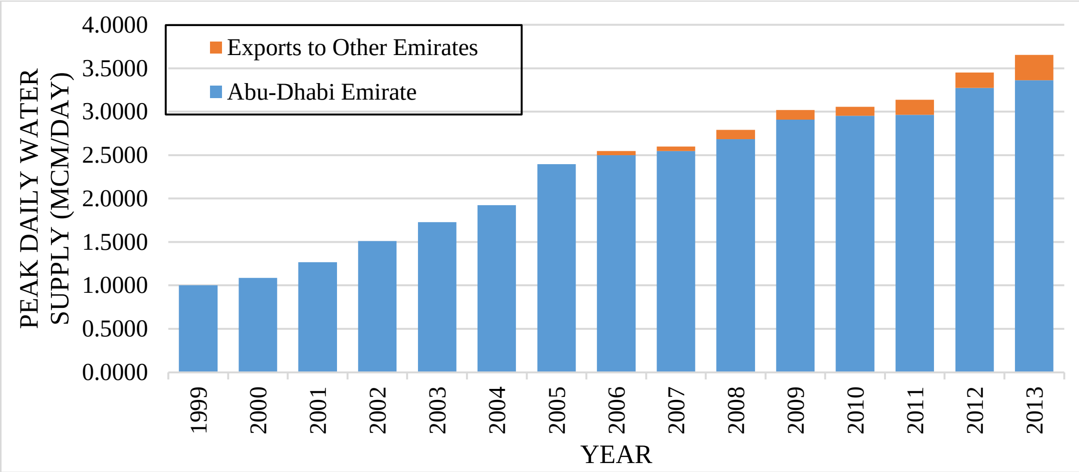


Figure 63: Peak daily water supply (ADWEC, 2015)

7.1 Groundwater

According to the latest statistics, the groundwater could be depleted in the next few decades. If the abstraction of groundwater still persists, and low the recharge rate of groundwater, the Abu-Dhabi Emirate will soon miss its only natural water resource. Furthermore, the agricultural and forestry sectors in Abu-Dhabi will face problems due to high water salinity levels and a sharp drop levels in the fresh groundwater (EAD, 2015).

The groundwater in Abu-Dhabi Emirate is a non-renewable resource. Hence, only 5% of annually water use is recharged. Environment Agency-Abu Dhabi (EAD) estimated that the usable groundwater (fresh and brackish water) will last for just over 50 years (EAD, 2015). The total reserves of groundwater in Emirate of Abu Dhabi in year 2012 were 639,750 MCM. Only 18% of all groundwater which was brackish is directly usable for agriculture. Just 3% is fresh that is protected as part of an emergency strategic reserve, whereas 79% is too saline and can only be used after treatment (Abu-Dhabi Food Control Authorities, 2015).

7.2 Desalination

With the decrease of groundwater reserves and increase in water demand; the amount of desalinated water has been increasing markedly in Emirate of Abu-Dhabi over the last few decades. Nevertheless, desalination plants are far from a sustainable development plan and this presents a huge economic and environmental challenge. Desalination plants require high energy which could be harmful to the environment causing air pollution through high emissions of CO_2. The brine, on the other hand, has negative impacts on marine ecosystems.

The consumption of desalinated water in Abu-Dhabi Emirate was increasing rapidly from 873 Mm^3, to 961.5 Mm^3 and 1,059 Mm^3 in years 2010, to 2011 and 2012, respectively (SCAD, 2015). The desalinated water demand exceeds Abu-Dhabi's current production capacity so, Abu-Dhabi imports from Al-Fujairah Plant. In instance, Abu-Dhabi desalination plants produced 883.4 MCM in 2012 and imported 201.3 MCM from Al-Fujairah Plant (SCAD, 2015).

7.3 Treated wastewater

Treated wastewater is a beneficial resource to address water shortage. Therefore, the treated wastewater plays an important role in water resources management in UAE and it is a significant resource for greening urban areas. Usually, the UAE wastewater treatment plants are activated sludge plants with tertiary treatment that consists of sand filtration and chlorination. There are several methods to treat wastewater which are used in UAE such as; activated sludge using surface aerators or fine bubble diffusers, aerated lagoons, aerated submerged media, UASB (up flow anaerobic sludge blanket) technology, sequential batch reactors, Package plants (based on activated sludge), and tricking filters.

Table 30 shows the amount of recycled water production, reused recycled water, and returned treated water to the environment. The table displayed that Abu-Dhabi Emirate used only 52% of the production in 2012, whereas discharged the remaining 48% to the environment (Abu-Dhabi Food Control Authorities, 2015).

Table 30: Abu-Dhabi Emirate's treated wastewater amounts (Abu-Dhabi Food Control Authorities, 2015)

	2010	%	2011	%	2012	%
Recycled water production (MCM)	246.6		243.1		265.4	
Reused recycled water (MCM)	126.3	51%	133.5	55%	138.8	52%
Returned to environment (MCM)	120.3	49%	109.6	45%	126.6	48%

7.4 Water Budget Model for Al-Ain City

The water balance is defined by the general hydrologic equation that is essentially a statement of the law of mass conservation as applied to the water cycle as shown in Figure 64. This equation is determined as; water inflow is equal to water outflow plus the change in balance. Because, water input and water output is not always in balance so, sometimes there is a change in water storage (Kumar, 2015).

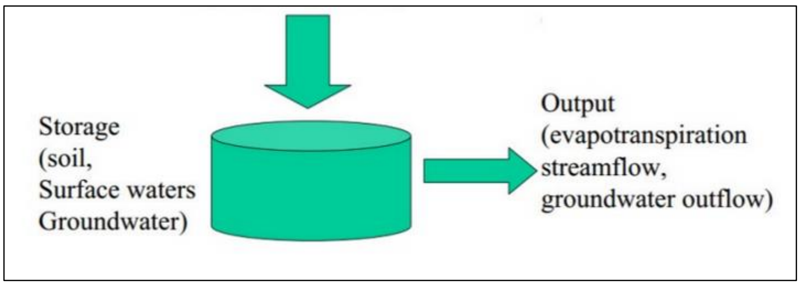


Figure 64: Diagram of the water balance model (Siddique, 2015)

Abu-Dhabi Transmission and Despatch Company (TRANSCO) is a company of Abu-Dhabi Water & Electricity Authority (ADWEA) and it is authorized by the Regulation and Supervision Bureau to own, develop, operate and maintain water transmission networks within the Abu-Dhabi Emirate and other Emirates in Northern region. TRANSCO undertakes each day a program for water production facilities to meet the water demand. Also, TRANSCO is responsible for the safe transmission of water from the producers, Independent Water and Power Producers (IWPPs), to the distribution company, which are Abu-Dhabi Distribution Company (ADDC) and Al-Ain Distribution Company (AADC). However, Figure 65 displays the layout of companies which responsible for produce, transmit and distribute the water from the water plants to the customers (TRANSCO, 2015). Furthermore, Figure 66 shows the percentage of each water production by plants of total production for Al-Ain city in the year 2013 (AADC, 2015).

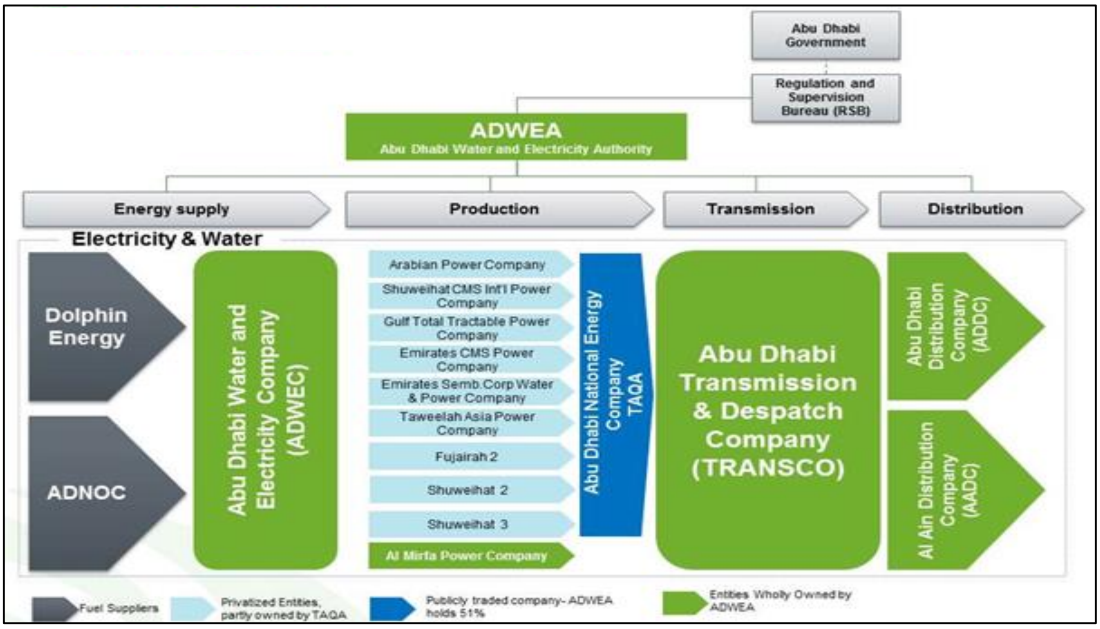


Figure 65: Sector layout of produce, transmit and distribute water (TRANSCO, 2015)

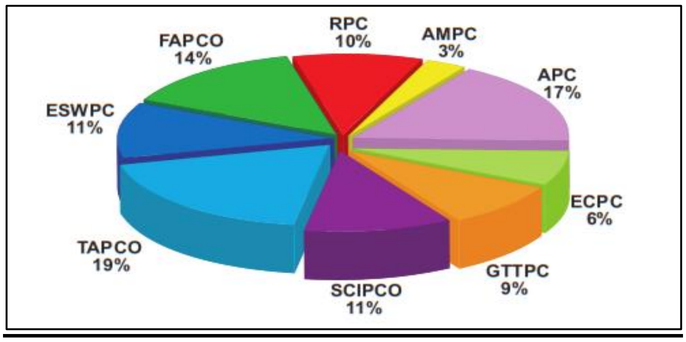


Figure 66: Water production by plants for Al-Ain city in the year 2013 (AADC, 2015)

Additionally, Figure 67 shows the hierarchy diagram of water budget model for Al-Ain City. Abu-Dhabi Emirate receives water from its seven production plants which are Taweelah Asia Power Company (TAPCO), Al Mirfa Power Company (AMPC), Emirates CMS Power Company (ECPC), Gulf Total Tractebel Power Company (GTTPC), Shuweihat CMS International Power Company (SCIPCO), Racing Power Company (RPC), and Arabian Power Company (APC). Also, Abu-Dhabi Emirate imports water from Fuijairah production plants which are Emirates Sembcorp Water and Power Company (ESWPC) and Fujairah Asia Power Company (FAPCO). Then, the water is distributed to three regions; Abu-Dhabi, Al Gharbia (Western Region), and Al-Ain. Each region distributes water to seven different sectors as shown in Figure 67.

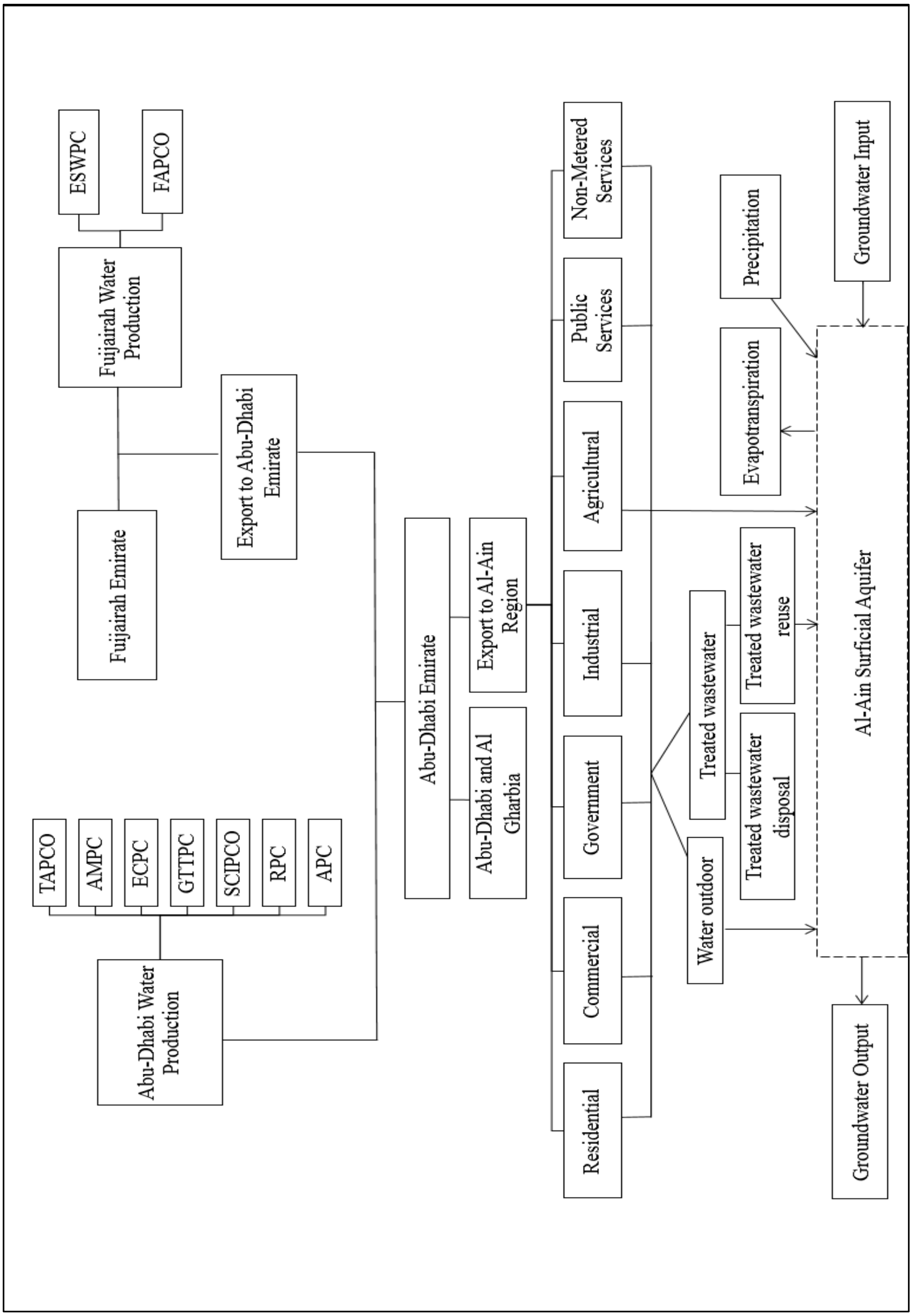


Figure 67: Water budget model for Al Ain city

7.4.1 Water Budget Model of the Year 2012

The following subsections are for describing the water budget model for Al-Ain city and the study model is carried out for the year 2012.

7.4.1.1 Water Consumption in Al-Ain City

The total water supply to A-Ain city in year 2012 was 287.92 MCMY (AADC). The water consumptions for all sectors in Al-Ain city, as indicated by AADC are as follows:

Table 31: Water consumptions in year 2012 (in MCM)

Year/ Sector	**Residential**	**Commercial**	**Government**	**Industrial**
2012	175.87	15.44	57.63	0.95
Year/ Sector	**Agricultural**	**Public services**	**Non-metered services**	
2012	29.51	3.46	5.06	

7.4.1.2 Evapotranspiration

The average evapotranspiration at Al-Ain city is 2.5 meters per year (Tourenq, 2015). The total irrigated area in Al-Ain city is obtained from Abu-Dhabi statistical Centre to be about 446 square kilometers (SCAD, 2015). So, the amount of evapotranspiration is equal to 2.5 m/day * 446 km^2 = 1115 MCMY.

7.4.1.3 Precipitation

The mean annual rainfall in Al-Ain city is 96.4 millimeters (Murad et al., 2012). The average rainfall surface area is estimated to be 25 × 45 = 1,125 square kilometers (Brook et al., 2006). The calculated amount of precipitation recharge to groundwater is equal to 96.4 mm * 1,125 km2 = 108.5 MCMY.

In a different way, the average total annual value of rainfall is 1090 MCM (Rizk and Alsharhan, 2003). As mentioned by Ministry of Environment and Water (2015) that 10% from precipitation will recharge to groundwater directly every year. The amount of precipitation recharge to groundwater is equal to 1090 MCMY * 0.10 = 109 MCMY.

So, the amount of precipitation recharge to groundwater obtained from previously mentioned resources is equal to 109 MCMY.

7.4.1.4 Wastewater Treatment

There are two wastewater treatment plants in Al-Ain city. The first one is Al Saad Wastewater Treatment Plant which is designed to treat a maximum capacity of 92,000 cubic meters per day. Another WWTP is Al Hamah Wastewater Treatment Plant, which it has a treatment capacity of 130,000 cubic meters per day and is designed for a population equivalent of 650,000 units. Therefore, the maximum capacity of two WWTP is 222,000 cubic meters per day.

The treated sewage is either re-used for landscaping irrigation or disposal of to surface ponds. Tables 32, 33, and 34 demonstrate the quantity of treated wastewater, treated wastewater for reuse, and treated wastewater for disposal, respectively, for Al-Ain region (SCAD, 2015).

Table 32: Quantity of treated wastewater (in MCM)

City/ Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Al-Ain	33.0	36.7	41.4	50.0	48.1	54.8	52.3	55.9	59.1	67.6

Table 33: Quantity of treated wastewater reuse (in MCM)

City/ Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Al-Ain	31.9	34.8	37.8	45.3	40.6	52.0	51.5	54.8	58.0	66.0

Table 34: Quantity of treated wastewater disposal (in MCM)

City/ Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Al-Ain	1.1	1.9	3.6	4.7	7.5	2.8	0.8	1.1	1.1	1.6

7.4.1.5 Groundwater Inflow and Outflow

The groundwater inflow and outflow of the Al-Ain city is found out from MOHAMED (2014) as the following:

- Groundwater inflow:

Al-Ain is located in the eastern region of Abu-Dhabi Emirate, inland on the border with Oman (EAD, 2006). Groundwater inflow is situated from the east of Al-Ain city, which is fed from Oman. The topography of the area between Al-Ain and Oman is unique and varies that include Al Hajar Mountains which shape many wadis. Darcy's Law is used to calculate the groundwater inflow from Oman as the following equation:

$$Q = K \, . \, A \, . \, I \qquad \text{(Eq. 15)}$$

Where:

Q = quantity of flow (m^3/s)

K = coefficient of permeability (m/s)

A = cross-sectional area to flow (m^2)

I = hydraulic gradient (I = ΔH/ΔL)

ΔH = difference in head (m)

ΔL = flow length across ΔH (m)

So, coefficient of permeability (K) in the eastern part of Abu-Dhabi Emirate equals 1 × 10E-05 m/s. Also, the average aquifer depth is 15 m and the length of study area is 25000 m. The ΔH and ΔL of the study area are 20 m and 4000 m, respectively. Substituting into the Darcy equation, the obtained value of groundwater inflow is 0.59 MCMY.

- Groundwater outflow:

Darcy's Law also is used to calculate the groundwater outflow but the difference is the groundwater outflow lies in the west of Al-Ain region. So, a different value is used for K in the western part of Al-Ain that equals 5 × 10E-06 m/s. in addition, the average aquifer depth is 25 m and the length of study area is 25000 m. Moreover, ΔH and ΔL of the study area are 20 m and 2500 m, respectively. Substituting into Darcy's equation, the obtained value of groundwater outflow is 0.79 MCMY.

All quantities of water calculated above are illustrated in Figure 68 and all numbers are in "million cubic meters per year".

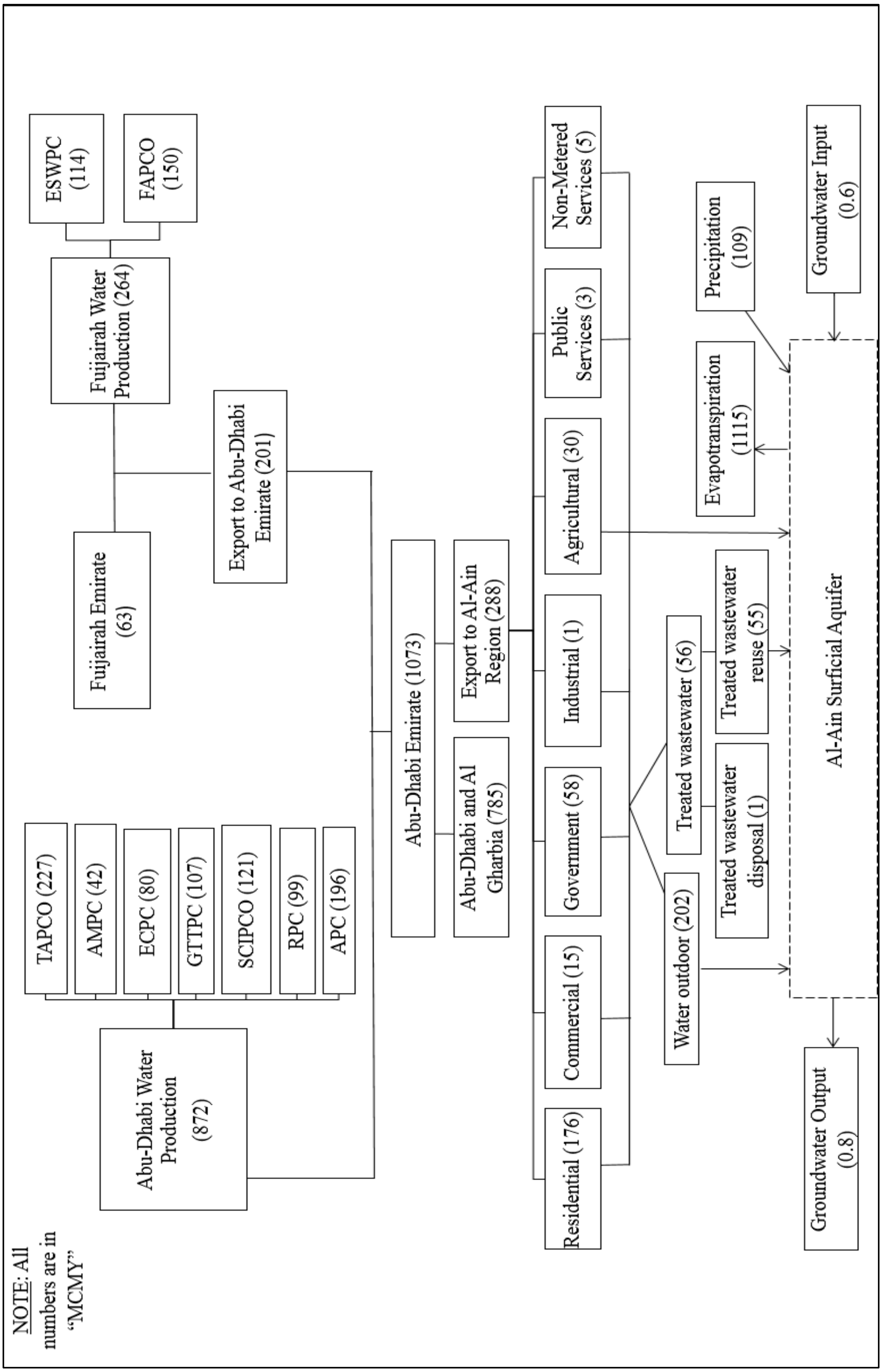


Figure 68: Water budget model for Al-Ain city of the year 2012 (MCMY)

Table 35 summarizes all calculated water input and output.

Table 35: Inflow and outflow from Al-Ain aquifer, year 2012 (MCMY)

Inflow		Outflow	
Groundwater Input	0.6	Groundwater Output	0.8
Precipitation	109	Evapotranspiration	1115
Agricultural	30		
Treated wastewater reuse	55		
Water outdoor	202		
Total	**397**	**Total**	**1116**
Balance = 719			

The results show that the effluent water from Al-Ain city is almost triple than the influent water. Regulation & Supervision Bureau demonstrates the water leakage that accounting for daily 7.4% of the total household water use, in year 2014 (RSB, 2015). The water outdoor leakage such as, irrigation for home garden, car washing, and swimming pool. The results also observed that the evapotranspiration has the highest amount of water. So, it is recommended to irrigate plants in evening to reduce losses from evaporation.

7.4.2 Water Budget Model of the Year 2030

Form the water demand forecasting scenarios (Chapter 6), the database 2 of both model 1 (Section 6.1.1.2) and model 2 (Section 6.1.2.2) are used to build the water budget model of the year 2030. The water consumptions for seven sectors for both models are shown in Table 36.

Table 36: Water consumptions for database 2 of model 1 and 2, year 2030 (in MCM)

Sectors / Water forecasting scenarios	Database 2, Model 1	Database 2, Model 2
Residential	385.63	439.83
Commercial	33.82	38.65
Government	125.54	147.09
Industrial	2.10	2.34
Agricultural	64.90	72.78
Public services	7.56	8.74
Non-metered services	11.07	12.78

The values of treated wastewater and treated wastewater reuse are estimated from SPSS equal to 119.9 MCMY and 118.9 MCMY, respectively. The following subsections show different scenarios of the water budget model for Al-Ain city of the year 2030 using database 2 with model 1 and model 2.

7.4.2.1 Water budget model using model 1

Five different water budget model scenarios were conducted for the year 2030 using model 1. Figure 69 illustrates the first scenario of water budget model for Al-Ain city of the year 2030 using database 2 with model 1. Table 37 shows all amounts of water inputs and outputs from the city in 2030 (scenario 1).

Table 37: Water inflows and outflows to/from Al-Ain aquifer in 2030 using model 1 (scenario 1) (in MCMY)

<table>
<tr><td colspan="2">Inflow</td><td colspan="2">Outflow</td></tr>
<tr><td>Groundwater Input</td><td>0.6</td><td>Groundwater Output</td><td>0.8</td></tr>
<tr><td>Precipitation</td><td>109</td><td>Evapotranspiration</td><td>1115</td></tr>
<tr><td>Agricultural</td><td>65</td><td colspan="2" rowspan="3"></td></tr>
<tr><td>Treated wastewater reuse</td><td>119</td></tr>
<tr><td>Water outdoor</td><td>446</td></tr>
<tr><td>Total</td><td>740</td><td>Total</td><td>1116</td></tr>
<tr><td colspan="4">Balance = 376</td></tr>
</table>

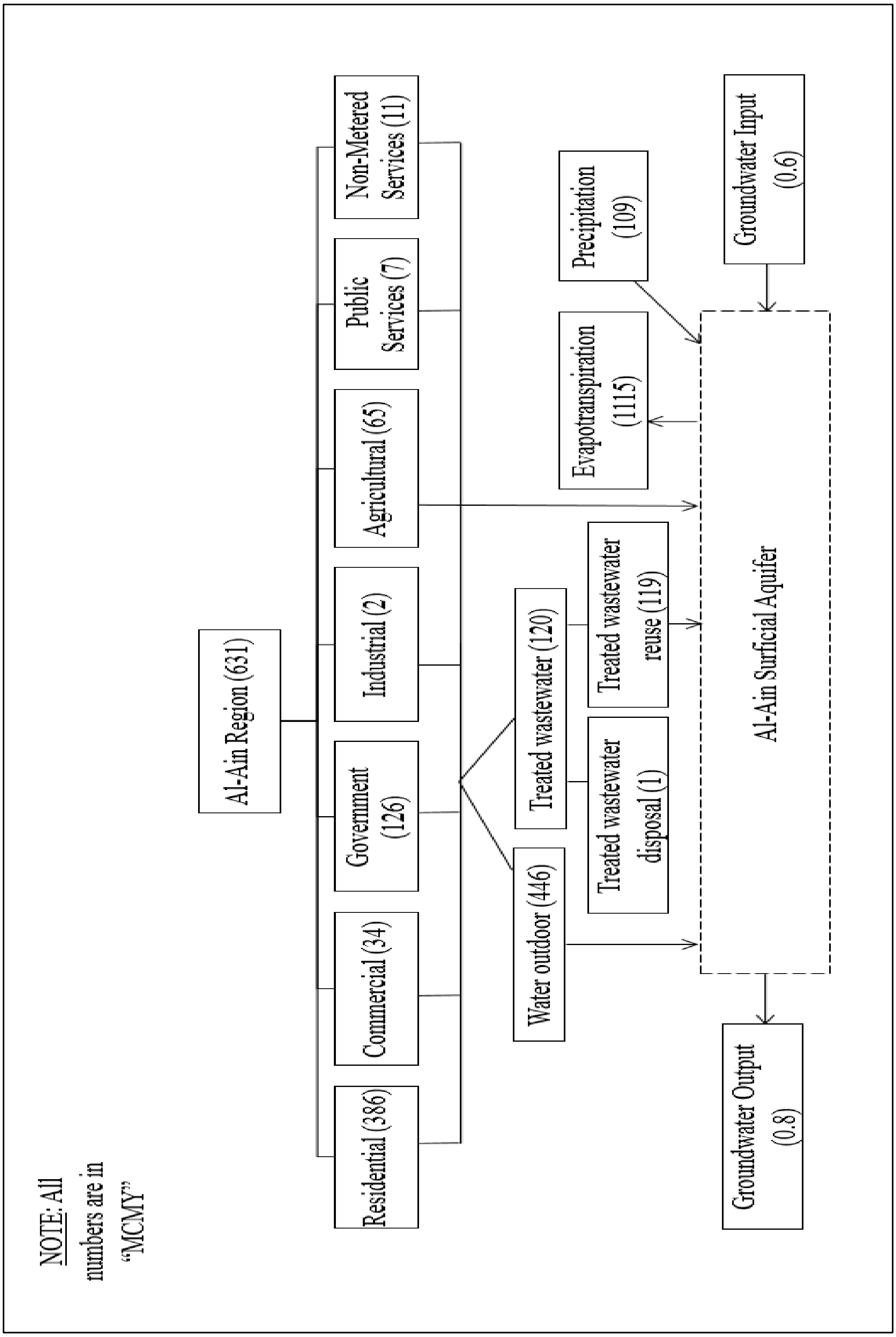


Figure 69: The first scenario of water budget model for Al-Ain city in 2030 using database 2 with model 1 (in MCMY)

Figure 70 illustrates the second scenario of water budget model for Al-Ain city of the year 2030 using database 2 with model 1. The amount of water demand for agricultural sector is the same as the quantity obtained from the water budget model of Al-Ain city for the year 2012.

Table 24 shows all amounts of water inputs and outputs from the city in 2030 using model 1 (scenario 2).

Table 38: Water inflows and outflows to/from Al-Ain aquifer in 2030 using model 1 (scenario 2) (in MCMY)

Inflow		Outflow	
Groundwater Input	0.6	Groundwater Output	0.8
Precipitation	109	Evapotranspiration	1115
Agricultural	30		
Treated wastewater reuse	119		
Water outdoor	446		
Total	**705**	**Total**	**1116**
Balance = 411			

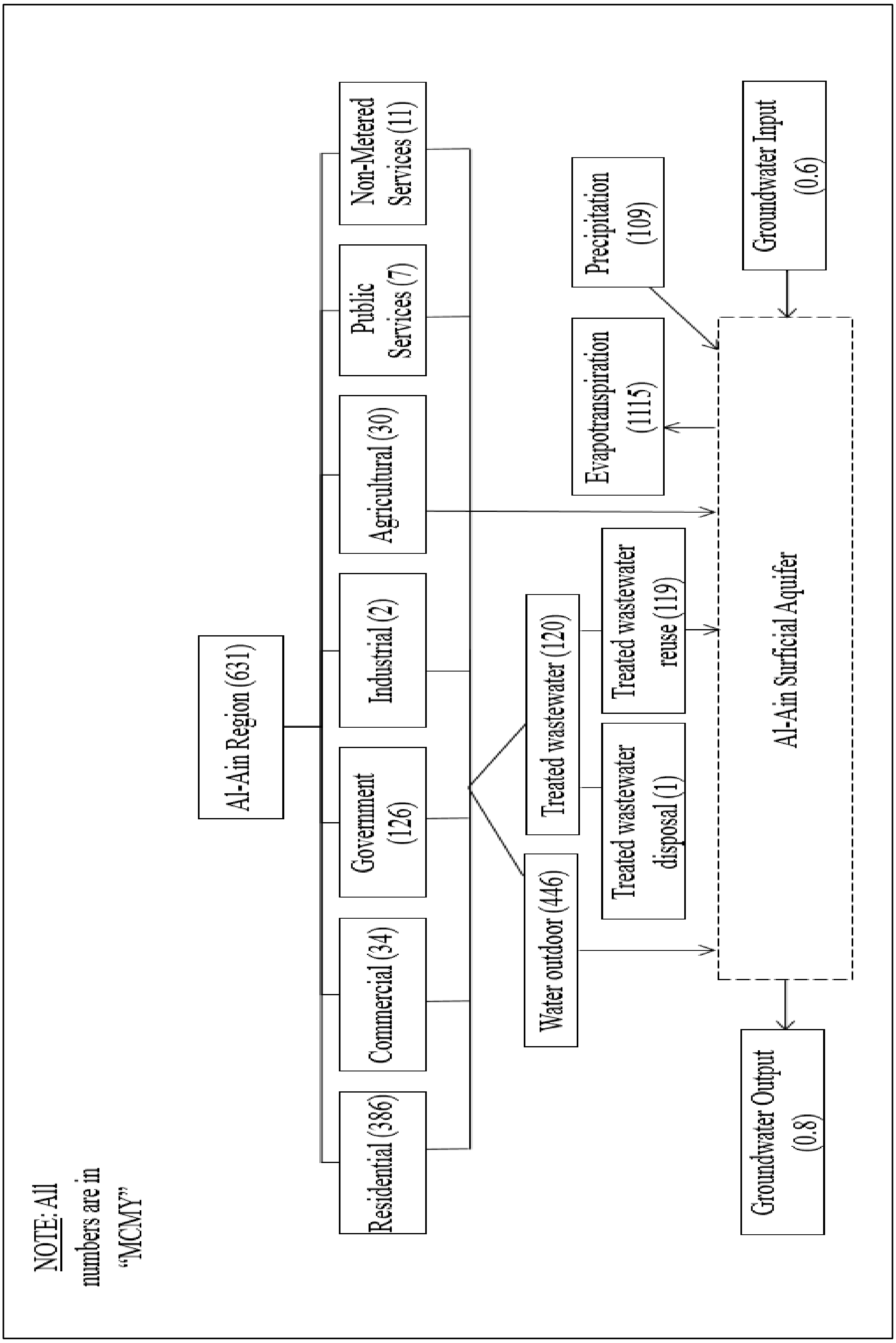


Figure 70: The second scenario of water budget model for Al-Ain city in 2030 using database 2 with model 1 (in MCMY)

Figure 71 illustrates the third scenario of water budget model for Al-Ain city of the year 2030 using database 2 with model 1. The quantity of predicted water for agricultural sector of the year 2030 is about 50% more than the quantity of water obtained for the agricultural sector in year 2012.

Table 39 shows all amounts of water inputs and outputs from the city in 2030 (scenario 3).

Table 39: Water inflows and outflows to/from Al-Ain aquifer in 2030 using model 1 (scenario 3) (in MCMY)

Inflow		Outflow	
Groundwater Input	0.6	Groundwater Output	0.8
Precipitation	109	Evapotranspiration	1115
Agricultural	15		
Treated wastewater reuse	119		
Water outdoor	446		
Total	**690**	**Total**	**1116**
Balance = 426			

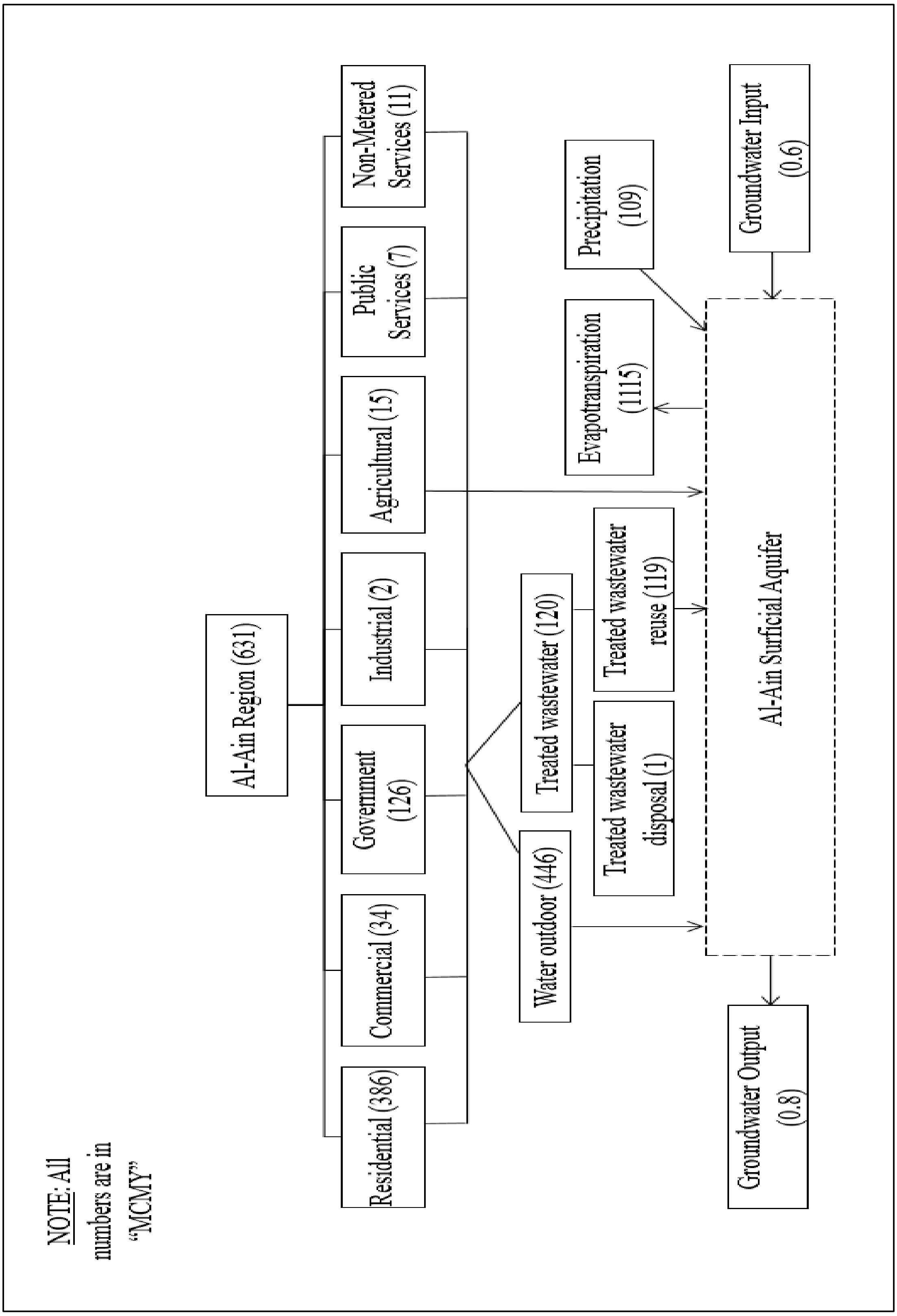


Figure 71: The third scenario of water budget model for Al-Ain city in 2030 using database 2 with model 1 (in MCMY)

Figure 72 illustrates the fourth scenario of water budget model for Al-Ain city of the year 2030 using database 2 with model 1. The amount of precipitation of the year 2030 is about 10% more than the amount of precipitation obtained in year 2012 (Almheiri, 2015).

Table 40 shows all amounts of water inputs and outputs from the city in 2030 (scenario 4).

Table 40: Water inflows and outflows to/from Al-Ain aquifer of the year 2030 using model 1 (scenario 4) (in MCMY)

Inflow		Outflow	
Groundwater Input	0.6	Groundwater Output	0.8
Precipitation	120	Evapotranspiration	1115
Agricultural	65		
Treated wastewater reuse	119		
Water outdoor	446		
Total	**751**	**Total**	**1116**
Balance = 365			

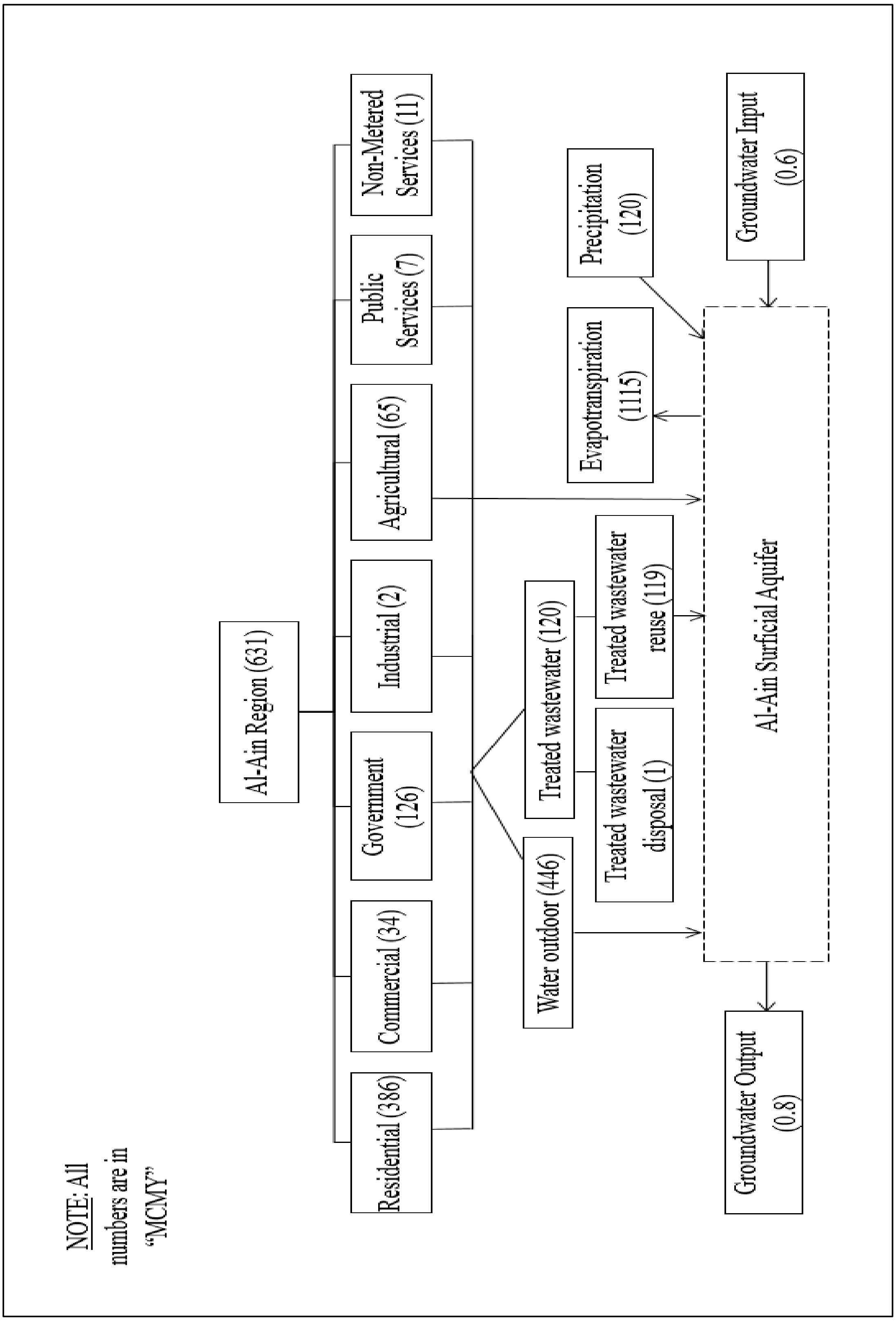


Figure 72: The fourth scenario of water budget model for Al-Ain city in 2030 using database 2 with model 1 (in MCMY)

Figure 73 illustrates the fifth scenario of water budget model for Al-Ain city of the year 2030 using database 2 with model 1. The amount of precipitation of the year 2030 is about 20% less than the amount of precipitation obtained in year 2012 (Almheiri, 2015).

Table 41 shows all amounts of inputs and outputs from the city in 2030 (scenario 5).

Table 41: Water inflows and outflows to/from Al-Ain aquifer in 2030 using model 1 (scenario 5) (in MCMY)

Inflow		Outflow	
Groundwater Input	0.6	Groundwater Output	0.8
Precipitation	87	Evapotranspiration	1115
Agricultural	65		
Treated wastewater reuse	119		
Water outdoor	446		
Total	**718**	**Total**	**1116**
Balance = 398			

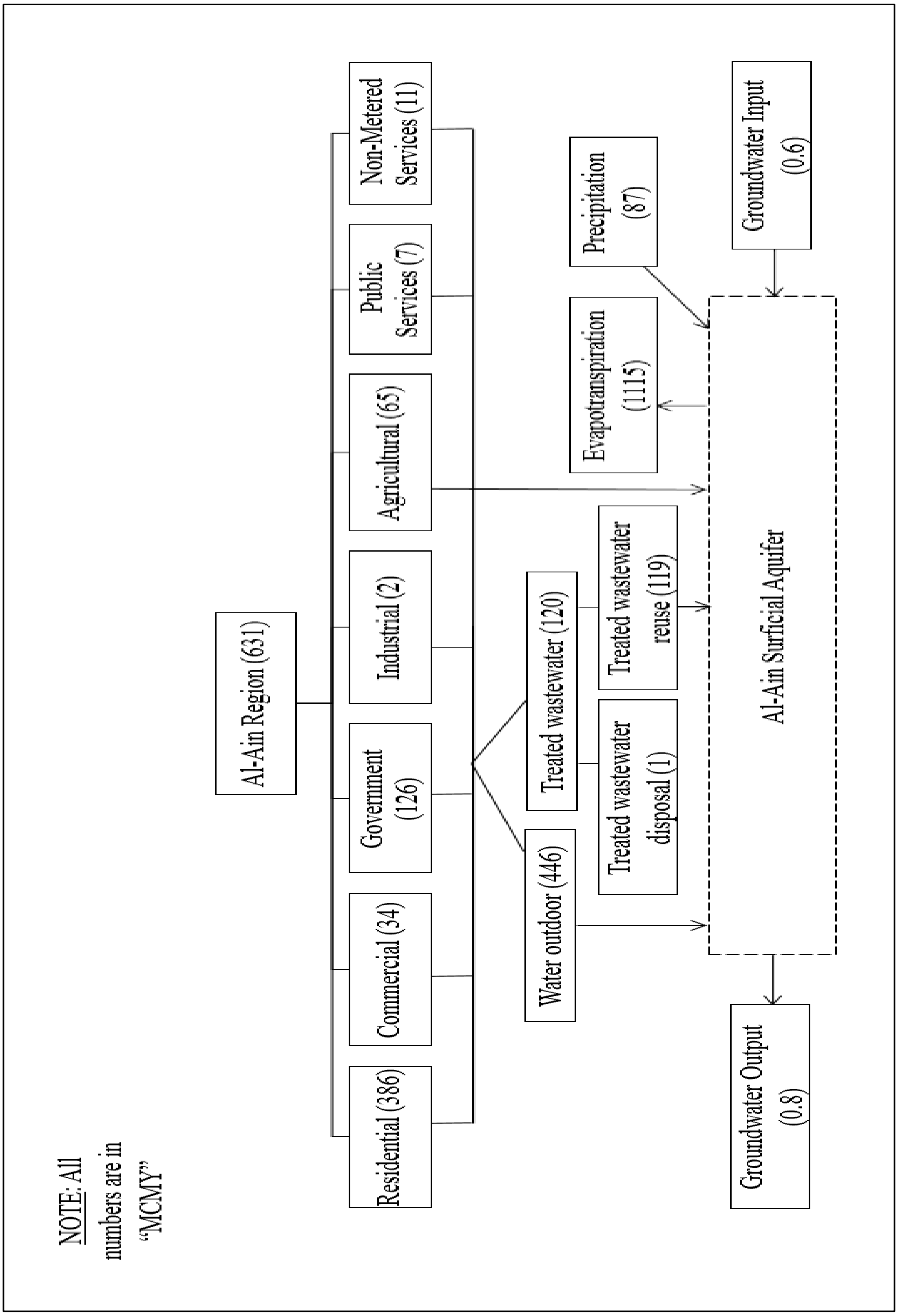


Figure 73: The fifth scenario of water budget model for Al-Ain city in 2030 using database 2 with model 1 (in MCMY)

7.4.2.2 Water budget model using model 2

Five different water budget model scenarios were conducted of the year 2030 using model 2. Figure 74 illustrates the first scenario of water budget model for Al-Ain city of the year 2030 using database 2 with model 2.

Table 42 shows all amounts of water inputs and outputs from the city in 2030 (scenario 1).

Table 42: Water inflows and outflows from Al-Ain aquifer in 2030 using model 2 (scenario 1) (in MCMY)

Inflow		Outflow	
Groundwater Input	0.6	Groundwater Output	0.8
Precipitation	109	Evapotranspiration	1115
Agricultural	73		
Treated wastewater reuse	119		
Water outdoor	529		
Total	**831**	**Total**	**1116**
Balance = 285			

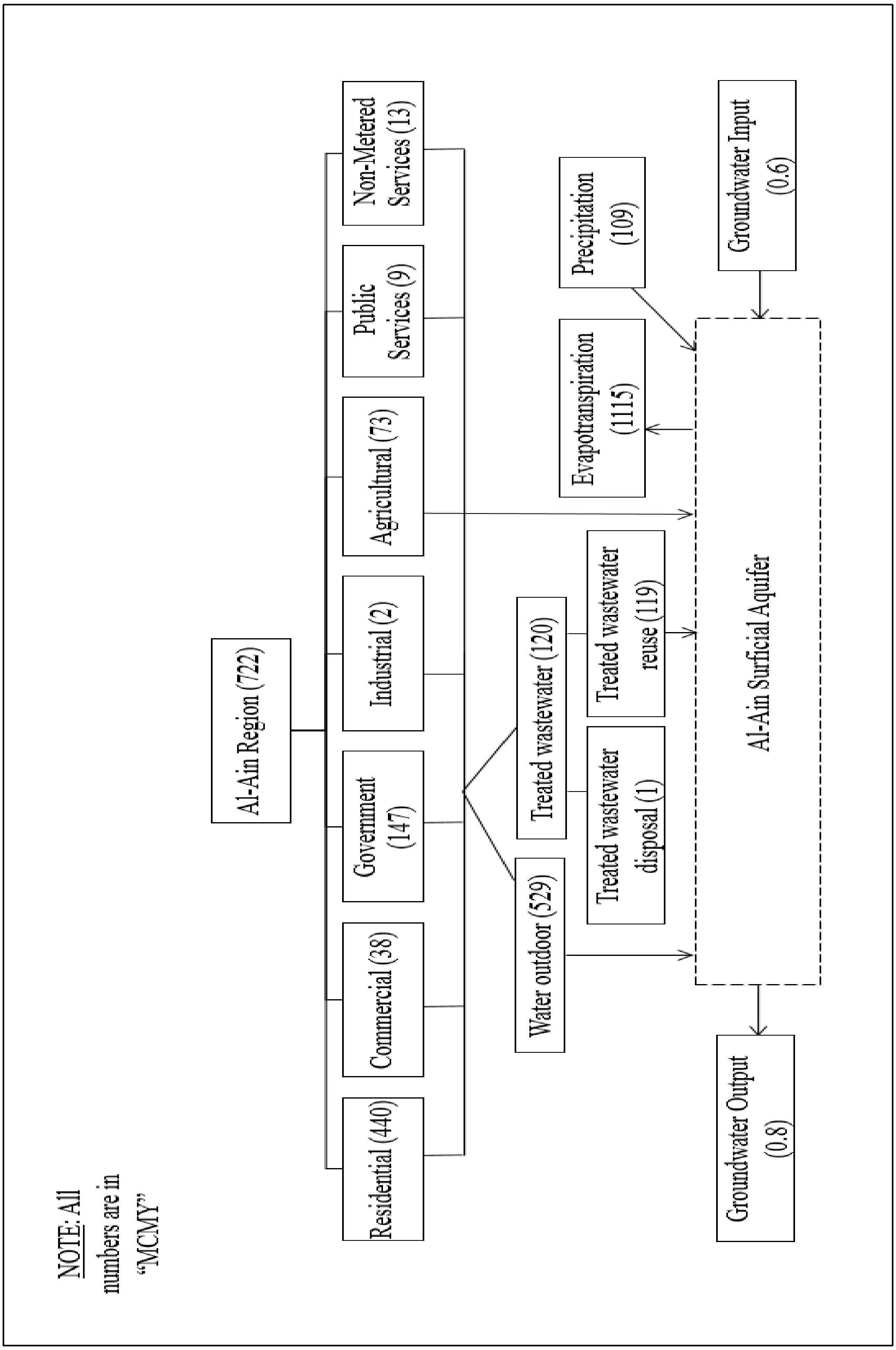


Figure 74: The first scenario of water budget model for Al-Ain city in 2030 using database 2 with model 2 (in MCMY)

Figure 75 illustrates the second scenario of water budget model for Al-Ain city of the year 2030 using database 2 with model 2. The amount of water demand for agricultural sector is the same as the quantity obtained from the water budget model of Al-Ain city for the year 2012.

Table 43 shows all amounts of water inputs and outputs from the city in 2030 (scenario 2).

Table 43: Water inflows and outflows from Al-Ain aquifer in 2030 using model 2 (scenario 2) (in MCMY)

Inflow		Outflow	
Groundwater Input	0.6	Groundwater Output	0.8
Precipitation	109	Evapotranspiration	1115
Agricultural	30		
Treated wastewater reuse	119		
Water outdoor	529		
Total	**788**	**Total**	**1116**
Balance = 328			

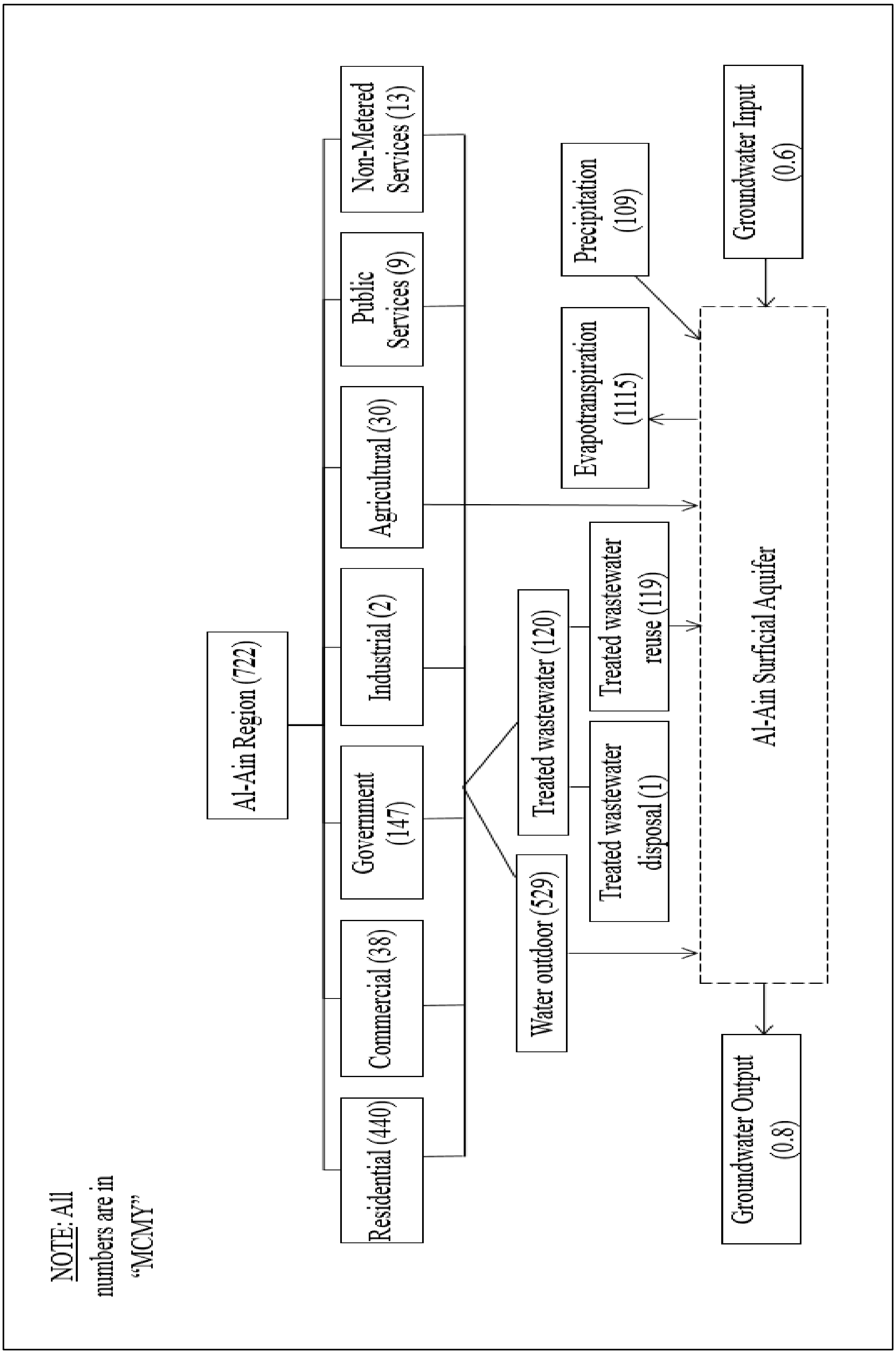


Figure 75: The second scenario of water budget model for Al-Ain city in 2030 using database 2 with model 2 (in MCMY)

Figure 76 illustrates the third scenario of water budget model for Al-Ain city of the year 2030 using database 2 with model 2. The quantity of predicted water for agricultural sector of the year 2030 is about 50% more than the quantity of water obtained for the agricultural sector in year 2012.

Table 44 shows all amount of water inputs and outputs from the city in 2030 (scenario 3).

Table 44: Water inflows and outflows from Al-Ain aquifer in 2030 using model 2 (scenario 3) (in MCMY)

Inflow		Outflow	
Groundwater Input	0.6	Groundwater Output	0.8
Precipitation	109	Evapotranspiration	1115
Agricultural	15		
Treated wastewater reuse	119		
Water outdoor	529		
Total	**773**	**Total**	**1116**
Balance = 343			

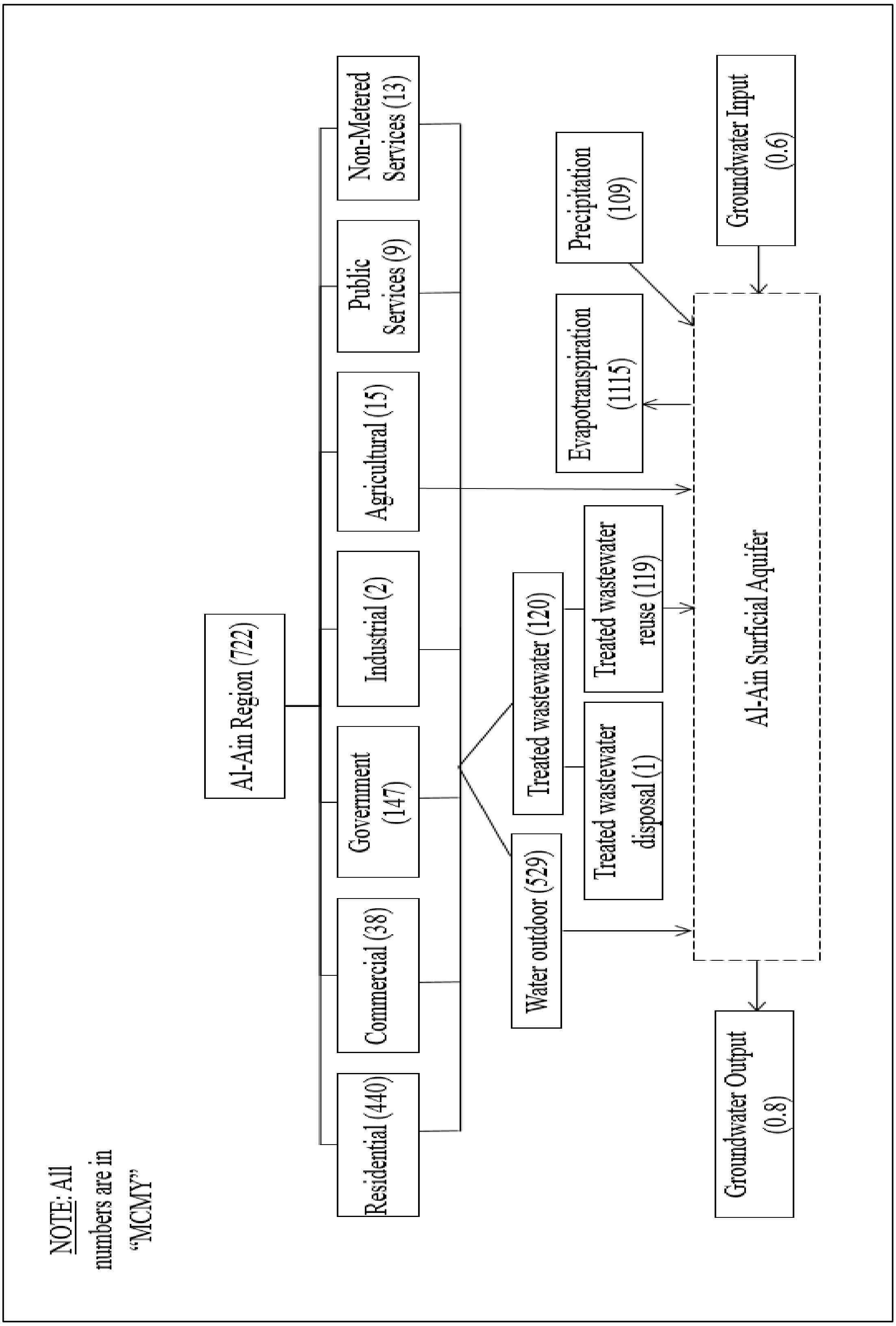


Figure 76: The third scenario of water budget model for Al-Ain city in 2030 using database 2 with model 2 (in MCMY)

Figure 77 illustrates the fourth scenario of water budget model for Al-Ain city of the year 2030 using database 2 with model 2. The amount of precipitation of the year 2030 is about 10% more than the amount of precipitation obtained in year 2012 (Almheiri, 2015).

Table 45 shows all amount of water inputs and outputs from the city in 2030 (scenario 4).

Table 45: Water inflows and outflows from Al-Ain aquifer in 2030 using model 2 (scenario 4) (in MCMY)

Inflow		Outflow	
Groundwater Input	0.6	Groundwater Output	0.8
Precipitation	120	Evapotranspiration	1115
Agricultural	73		
Treated wastewater reuse	119		
Water outdoor	529		
Total	**842**	**Total**	**1116**
Balance = 274			

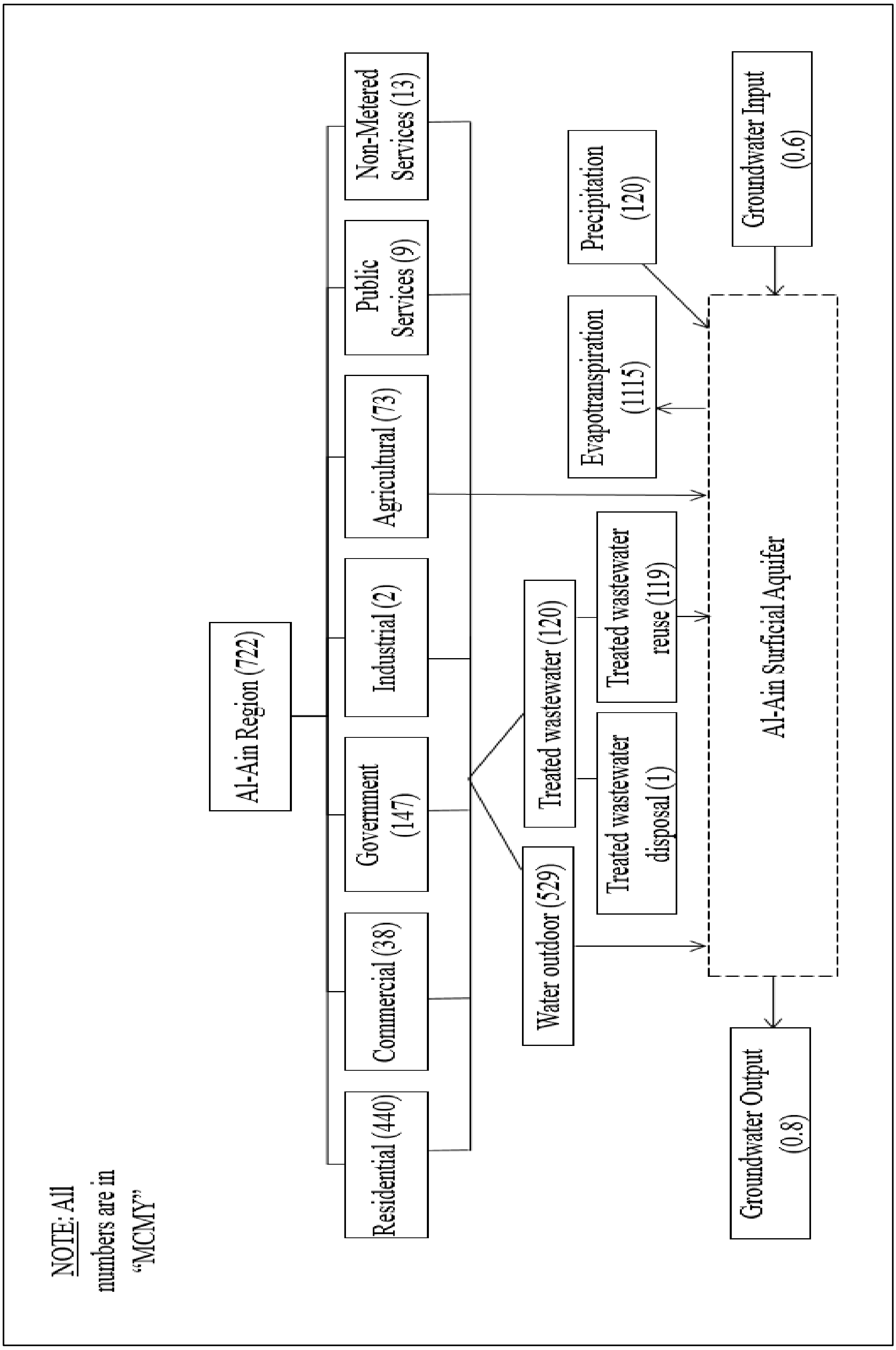


Figure 77: The fourth scenario of water budget model for Al-Ain city in 2030 using database 2 with model 2 (in MCMY)

Figure 78 illustrates the fifth scenario of water budget model for Al-Ain city of the year 2030 using database 2 with model 2. The amount of precipitation of the year 2030 is about 20% less than the amount of precipitation obtained in year 2012 (Almheiri, 2015).

Table 46 shows all amount of water inputs and outputs from the city in 2030 (scenario 5).

Table 46: Water inflows and outflows from Al-Ain aquifer in 2030 using model 2 (scenario 5) (in MCMY)

Inflow		Outflow	
Groundwater Input	0.6	Groundwater Output	0.8
Precipitation	87	Evapotranspiration	1115
Agricultural	73		
Treated wastewater reuse	119		
Water outdoor	529		
Total	**809**	**Total**	**1116**
Balance = 307			

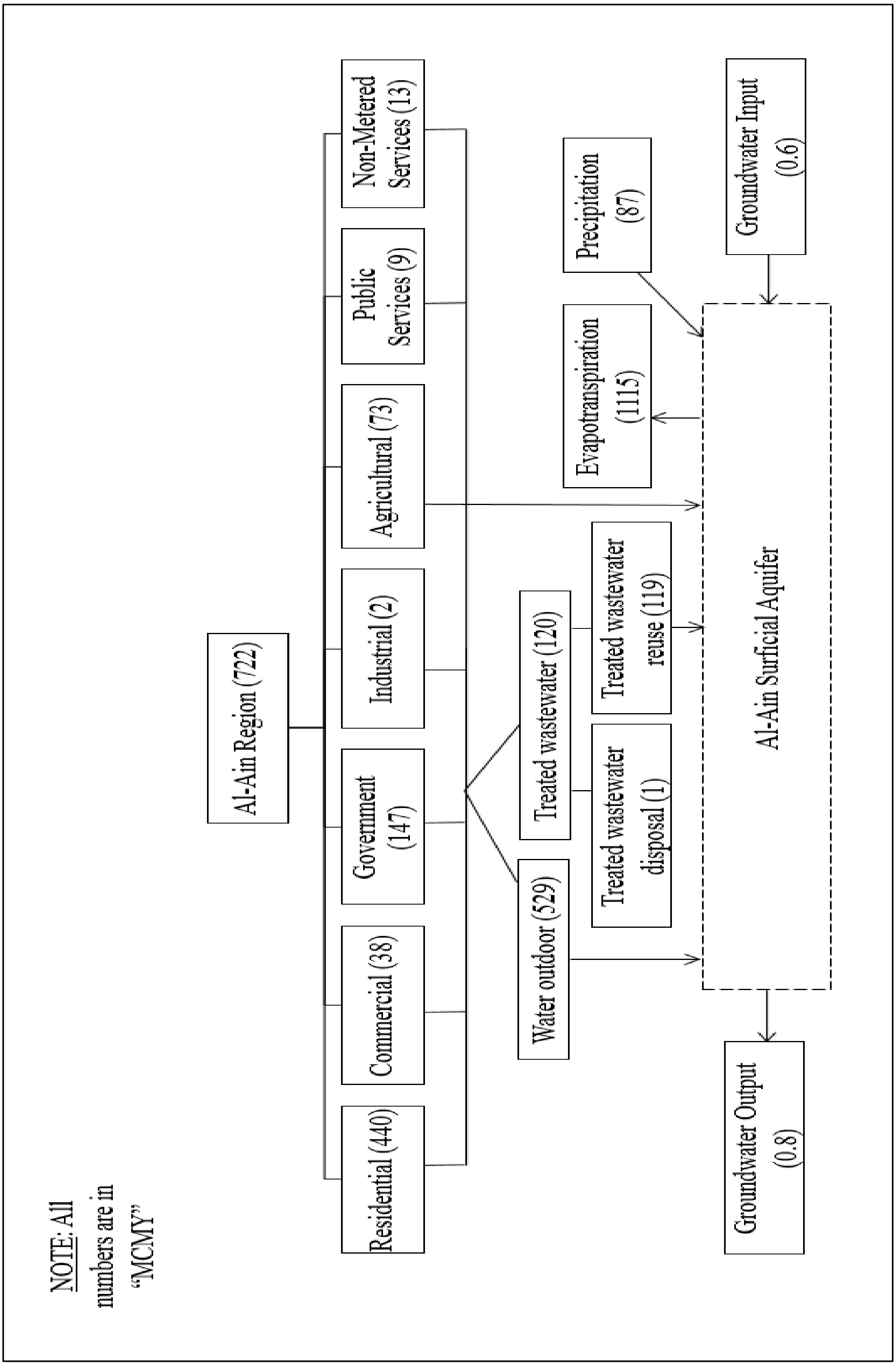


Figure 78: The fifth scenario of water budget model for Al-Ain city in 2030 using database 2 with model 2 (in MCMY)

7.4.2.3 A Comparison of Results

Scenario 1 shows that the effluent water from the city is about 50% than the influent water by model 1, while it is almost 35% in model 2. In both models, scenario 4 was observed the least amount of water balance, whereas, scenario 3 was observed the highest amount of water balance. On the other hand, scenario 5 was observed less amount of water balance than scenario 2.

Due to the large increase of the population in Al-Ain city, as a result of the expansion in the economic projects and the employment of foreign labor, significant increase in water demand is predicted. The water table has steadily risen in recent years due to artificial recharge of groundwater from irrigation and disposal of treated wastewater. Increase of water table causes increase in the salinity of soil, it has a negative effect on houses foundations, could cause subsurface caving, and may cause collapse of structures.

Chapter 8: Conclusions

This study presented the prediction of water demand for Al-Ain city from 2013 to 2030. Additionally, this study described the water budget model for Al-Ain city for the years 2012 and 2030. Several available databases are used in this study during the periods of 1998 – 2012 including water consumption by sectors/categories, population size and average temperature. Based on the SPSS program simulations, the population was only the significant independent variable in this study, whereas the average temperature and rainfall amount were not significantly correlated to water consumption. The model calibration and prediction were performed for two different models, which are Constant Use Rate Model and Linear Forecasting Model, using IWR-MAIN program. The first model depends directly on the population size of a city, whilst the second model depends on the population size, model coefficient (β), and model intercept (α). The two models' calibrations were conducted using four databases; namely, total annual water use, annual water use for seven sectors, total monthly water use, and monthly water use for seven sectors. The seven sectors are agricultural, residential, non-metered services, commercial, government, industrial, and public services. Three main groups of forecasting scenarios were implemented in this study, including base scenarios using IWR-MAIN, population growth scenario, and water losses scenario. The base scenarios contain prediction based on models 1 and 2. The population growth scenario contained four sub-scenarios and the water losses scenario contained ten sub-scenarios.

Some reasons might be a part of uncertainties in the provided data by AADC which is the uncertainties in reading and recording procedures i.e., if a reading was not taken for the particular month, an average consumption reading is carried out. Generally, the uncertainty in the projected water demand increases with the increase of projections periods. The uncertainty in the forecast of water demand is embedded in the prediction of population growth either yearly or monthly. Therefore, the results depend on the accuracy of the assumptions.

In Model 1, the constant per capita rate for the best base year is used to predict future water demands. AARE, ARMSE, and SDARE were calculated to select the best base year for forecasting the water demand. The expected future population was modeled in this study by exponential regression using SPSS program. It was noticed that the population size will become almost double by 2030. Model 1 is used with database 1 (total annual water use) and database 2 (annual water use for each sector). It was found that the water demand in year 2030 will be almost double that of the year 2015. Water demand in August is found to be the largest. Using database 4 with model 1 revealed that August has the highest water demand for commercial, government, and non-metered services sectors, while agricultural, industrial, public services, and residential sectors, have the highest water demand in October, June, April, and March, respectively.

The linear forecasting model was the second method used in this study. This model uses a multiple regression analysis. Results of this model indicated that the total water demand for database 1 is expected to increase by 45% in year 2030. For database 2, the residential sector has the largest water demand with an estimated share of 61% of the total water demand by the year 2030. The governmental and agricultural sectors have an estimated share of 20% and 10%, respectively. Another 9% are estimated for the rest of four sectors. Database 3 showed that the maximum water demand occurs in August from 2013 to 2025 and in September during 2026 - 2030. Database 4 showed that the highest water demand for agricultural sector occurs in October. For commercial and government categories, the highest water demand expected to be in August. During the years 2013 - 2016, the residential and non-metered services sectors have the lowest water demand in October. Also, industrial sector is estimated to have the lowest water demand in months of June and August during the years of 2013 – 2021 and 2022 – 2030, respectively. The minimum water demand using database 4 is expected to be in February.

The verifications of models 1 and 2 are conducted using database 1 with base years 2008 and 2010, respectively. The verification results show that linear forecasting model is more accurate than constant use rate model. In addition, the results show that the best base year for database 1 using models 1 and 2 is year 2010, as obtained from model calibration. These results ensure the correct implementation of IWR-MAIN program.

The results comparison between two forecasting models shows that model 2 has higher forecasting results than model 1. In both models, the forecasting results of database 1 is equal to the results of database 2, while the results of database 3 and database 4 are the same. In both models, the forecasting results using database 1 is equal to the results using database 2, while the forecasting results using database 3 and database 4 are the same. The results also show that the water demand forecasting using model 2 is higher than model 1 because the model 2 depends on the model coefficient and intercept (β, α), while model 1 depends directly on the population growth.

This study also illustrated population growth scenarios including four sub-scenarios. The first scenario discussed the impact of natural population growth on water demand in Al-Ain city (data provided by AADC). The impact of immigration to cover labor needed for expected mega-projects in Al-Ain city is studied in the second scenario (S2). The expected increase in visitors to Al-Ain city which are expected to spend two weeks and four weeks are simulated in scenarios three and four, respectively. The annual water demand projections for the four scenarios increased in year 2030 by 433, 492, 477 and 490 MCM, respectively, compared to water use in year 2013.

This second set of scenarios includes ten different water losses sub-scenarios. Data received from Al-Ain Distribution Company (AADC) indicates that losses through the water distribution in Al-Ain city to be around 20%. Three groups of sub-scenarios are simulated, each contains three sub-scenarios. These sub-scenarios reflect three deterioration rates of the distribution system; including increased water losses by1% per 3 years, 2% per 3 years, and 1% per 1 year. In the first group, it is assumed that no rehabilitation of water distribution systems will take place before 2030. So the water losses percentages are expected to increase until they reach 25%, 30%, and 35%, in 2030 in the three sub-scenarios, respectively. For the second and third groups of sub-scenarios, a 5-year and 10-year rehabilitation plans, respectively, for the water distribution system are simulated to start in year 2015. Therefore, the reduction of water losses is expected to reach 10% in year 2020 in scenarios S8, S9, and S10; and in year 2025 in scenarios S11, S12, and S13. A 15-year rehabilitation plan is simulated in scenario 14. The highest water demand is simulated in scenario 7. The first nine scenarios show that the minimum amount of water demand is obtained from scenarios 8, 9, and 10 during 2016 – 2022. The lowest water demand in scenarios 11, 12, and 13 are obtained in year 2025. Scenario 11 has the lowest water demand during 2026 to 2028, however, scenario 13 has the lowest demand in 2026. Adapting a longer rehabilitation plan results in less simulated water demand.

Water budget models for Al-Ain city of the years 2012 and 2030 were studied in Chapter 7. Five different scenarios were conducted to obtain the water budget model of the year 2030 using water forecasting scenarios created by models 1 and 2 for database 2. The first scenario of water budget model of the year 2030 using database 2, while the second scenario contain an amount of water demand for agricultural sector is same as the quantity obtained from water budget model of the year 2012. The third scenario contain the quantity of predicted water for agricultural sector of the year 2030 is 50% more than the quantity of water for agricultural sector obtained in year 2012. Whereas, the fourth scenario contain an amount of predicted precipitation of the year 2030 is 10% more than the amount of precipitation obtained in year 2012, and the fifth scenario contain the amount of predicted precipitation of the year 2030 is 20% less than the amount of precipitation obtained in year 2012. Scenario 1 shows that the effluent water from the city is around 50% than the influent water by model 1, while it is almost 35% in model 2. In both models, scenario 4 was observed the least amount of water balance, whereas, scenario 3 was observed the highest amount of water balance. On the other hand, scenario 5 was observed less amount of water balance than scenario 2.

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